UNIVERSITY OF CALIFORNIA, SAN DIEGO

Economics of Intellectual Property:
Valuation, Strategy and Policy Impact

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requirements for the degree
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in

Economics

by

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2012

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The dissertation of Kirti Gupta is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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Chair

University of California, San Diego

2012

DEDICATION

To Paolo, for being the most avid supporter, the most exacting critic, and for always being there.

EPIGRAPH

One gob, one gap, one gulp and gorger of all! — *James Joyce*

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ABSTRACT OF THE DISSERTATION

Economics of Intellectual Property:
Valuation, Strategy and Policy Impact

by

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As Intellectual Property (IP) increasingly acquires a central role in today's knowledge economy, tools for valuation of IP assets for facilitating new markets for their trade, and for effective generation and management of IP assets is becoming central to firms' strategies. An increase in patenting activity and patent litigations have also led to important policy debates regarding the potentially harmful impact of the patent system and proposed reforms to it. In this thesis, I explore how fundamental questions around valuation of patents, strategic management of patents, and policy issues around the patent system can be addressed via empirical econometric analysis of data. First, I explore the relationship between publicly available patent characteristics and the measure of patent values. Using patent

specific value estimates, I find that the number of received citations explains the value measure far more than other indicators such as the citations made, number of claims, countries in which a patent is applied, and prosecution effort. I also find that focusing on specific technology areas is important for a more precise understanding of the indicators of patent values. Second, I estimate whether the value of innovations can be predicted to any degree early in their life cycle. I exploit the establishment of screening processes by organizations to predict of value of innovations before filing them as patents, to save high costs incurred in pursuing potentially non valuable innovations with the patent offices. I find that despite a large effort expended by groups of leading subject matter experts, the prediction power of the value of early innovations remains weak. This finding suggests that innovations are unpredictable by nature, even to those with the best state-of-the-art knowledge in the area of innovation, and explains why we observe a highly skewed distribution of their value in general. Third, I analyze how the patenting behavior of start-up firms is related to patent thickets, i.e., by the number of existing IP rights holders and by the amount of dispersion of those rights, while controlling for observable firm and market characteristics. I investigate the impact of patent thickets on both quality and quantity of patents produced by start-up firms founded between 2001-05 in rapidly evolving semiconductors, digital communications, and telecommunications industries. I find that on average, start-up firms file more and higher quality patents in technology areas with higher number of existing IP rights holders.

Chapter 1

Introduction

Today's knowledge economy has shifted its weight towards Intellectual Property (IP) and intangible assets in all industries. For the largest firms in the United States, IP and other intangible assets have exploded as a percentage of S&P 500's market value from an average of 16.5% in 1975 to almost 80% in 2005. The most common form of IP is a patent – a grant made by the government that confers upon the creator of an invention the sole right to make, use, and sell that invention for a set period of time. The number of patent applications in the U.S. has risen exponentially since the 1980s, with an average year-over-year growth of $\approx 6\%$ from 1985–2010. The sudden rise of the importance of IP has generated new markets for trading of IP rights, requiring tools for valuation of these assets. Firms have started paying more attention towards generating and effectively managing their IP assets. Finally, the sudden activity in the IP arena has led to several policy debates, in particular about the need for patent reform.

In this thesis, I take steps towards understanding the methods for valuation of patents, best practices for management of innovative ideas that potentially convert into patents, and the role of patent rights in fostering or hindering future innovation.

The growth in activity of IP has witnessed the generation of a marketplace for IP. Firms no longer just rely on producing patents, but also purchasing or selling patent rights to each other[1]. In late 2000's, the markets also started witnessing

[1] The rise of markets for IP saw auctioning entities such as Ocean Tomo, and patent aggregators

large acquisitions by firms primarily driven by patents[2]. All these transactions require methods for valuing patents and patent portfolios. However, patent valuation has been called a "black art" in the industry as patent values display a highly skewed distribution. Improved valuation methods can lower the cost of capital ex-ante, as well as reduce dead-weight losses since high cost paid for a patent portfolio by a firm for offensive or deterrence strategy may ultimately translate into higher cost of its products to consumers. The first paper of my dissertation is focused on addressing the problem of patent valuation. I build upon the previous literature that has established that patent counts are known to be unreliable estimates of patent portfolio values. I examine the relationship between publicly available patent factors (e.g., citations) and value of patents with the help of a unique sample data-set, observing the valuation of individual patents from a group of firms in a specific technology area. I find that the number of received citations explains the value measure far more than other indicators such as the citations made, number of claims, countries in which a patent is applied, and prosecution effort. I also find that focusing on specific technology areas is important for a more precise understanding of the indicators of patent values.

The academic and management literature has recorded a "new era of patenting and licensing", started by Texas Instruments (mid-80s) and IBM's (mid-90s) campaigns to monetize their IP portfolios. Indeed, total revenues generated from licensing of IP rights skyrocketed in U.S. from \$15b in 1990 to over \$250b in 2011. The pressure faced by firms to produce more patents poses a strategic challenge: how to manage the rising cost of patenting. The challenge is better understood by noting that the patent fee structure at most patent offices is "front loaded", in other words, a larger proportion of the lifetime fee for obtaining a patent is incurred during the first 4-5 years of a patent's 20-year long life, precisely when the uncertainty in a patent's value is the highest. In the second chapter of my

such as Intellectual Ventures, Acacia and the like in the early 2000's, to facilitate a marketplace for patents.

[2]Notable acquisitions in the high-tech industry include the acquisition of Novell's portfolio of 882 patents for \$450m by Microsoft, Apple, Oracle and EMC[2], Nortel's portfolio of 6000 patents and applications for \$4.5b by Apple, Microsoft, Sony and RIM, and of Motorola Mobility with a portfolio of 24,500 patents and applications for \$12.5b by Google Inc.

dissertation, I examine whether the value of innovations can be predicted early in their life-cycle. As the IP filed by firms has been rising exponentially across the board, several firms have started establishing a screening process for reviewing innovations prior to filing them, to try and reduce the cost of converting the potentially less valuable innovations into patents. I examine if highly innovative firms can employ a group of qualified subject matter experts to predict the value of innovations early in the IP life-cycle, before a large proportion of the total cost of acquiring a patent has been incurred. I discover that value of innovations is indeed unpredictable by nature, explaining why several works have observed highly skewed distribution of patents.

The rise in the patenting activity has been accompanied by a sharp rise in patent related litigations, and there is a growing concern in the recent years that patents themselves may be becoming harmful for the innovative process. In particular, in complex technologies where one product is covered by hundreds of patents, the argument is that strategic patenting activity creates a "thicket" of fragmented property rights that impedes R&D activity by constraining firms to operate without extensive licensing of complementary technologies. In the third chapter of my dissertation, I analyze how the patenting behavior of start-up firms is related to patent thickets, i.e., by the number of existing IP rights holders and by the amount of dispersion of those rights, while controlling for observable firm and market characteristics. I investigate the impact of patent thickets on both quality and quantity of patents produced by start-up firms founded between 2001-05 in rapidly evolving semiconductors, digital communications, and telecommunications industries. I find that start-up firms in areas with a higher number of existing IP rights holders produce a higher number and higher quality of patents.

The thesis is organized as follows. Chapter 2 discusses the work on exploring the indicators of patent values. Chapter 3 presents a case study investigating whether the value of innovations can be predicted early in their life-cycle. In Chapter 4, results for understanding the relationship between patenting strategies of startup firms and patent thickets are discussed.

Chapter 2

Exploring the Indicators of Patent Values

Patent values display a highly skewed distribution and therefore simple patent counts are known to be inaccurate measures of innovative output of firms and entities. Studies in the past have tried to explore the relationship between publicly available patent characteristics and the measure of patent values. However, proxies for the value of aggregate patents portfolios such as stock market prices of firms have been used to establish these relationships. This paper employs a sample data set across a set of firms consisting of patents on which significant resources have been employed for assigning value ratings to individual patents, rather than a portfolio of patents. In addition, by focussing on a specific industry, issues regarding the heterogeneity of patent characteristics (such as citations) across industries are avoided. This study finds that the number of received citations explains the value measure far more than other indicators such as the citations made, number of claims, countries in which a patent is applied and prosecution effort. The results demonstrate that focusing on specific technology areas is important for a more precise understanding of the indicators of patent values.

2.1 Introduction

Publicly available information on patents has provided a rich source of data for economists studying the fields of innovation and technological change. Patents are the only good proxy for the inventive output of firms that offer a wide coverage – over every field of innovation and over a long time period. In the United States (U.S.) alone, patents have been granted since the 18th century and currently the total number of U.S. patents exceed 6 million, with a rate of 150,000 added per year to the stock, across a wide variety of technological areas.

Several early studies relied on simple patent counts as measure of innovative output of firms, by tying them to firm characteristics such as research and development (R&D) expenditures, productivity and growth (Schmookler (1952), Scherer (1982), Bound *et al.* (1984), Pakes and Griliches (1984)). However, as the patent literature advanced, it was empirically demonstrated that innovations vary enormously in their technological and economic value and the distribution of such values is extremely skewed. For example, only thirty-seven percent of U.S. patens are maintained (or kept alive) by their owners until the end of their term (Berman (2002)), and an even smaller percentage are maintained until the end of term in European countries, where the payments for maintaining patents rise as they age (Schankerman and Pakes (1986)). Additionally, ninety-nine percent of patents are never enforced via filing a law-suit by their owners (Lemley (2001)).

In light of surging patent counts[1] in the U.S., paralleled by an increase in the relevance of intangible assets for firm values in the last two decades, this posits a serious question for researchers, firm strategists and businesses – how to identify potentially valuable patents from a large and ever growing pool of patents? Learning the severe limitation of simple patent counts in the extent to which they could capture the underlying heterogeneity of patent values, researchers have been exploring the use of other data items contained in patents themselves. In particular,

[1]The count of patent applications and grants have exploded in the U.S. since the early 1980s (USPTO (US Patent and Trademark Office) data, Jaffe and Lerner (2004)). The reasons for this have been cited to be the establishment of Court of Appeals for the Federal Circuit (CAFC) in 1982 to strengthen patent rights (Gallini (2002)), and the new responsibility of USPTO for generating its own funds via the fee it collects, rather than operating as a federally funded agency (Jaffe and Lerner (2004)).

patent citations have been suggested as one possibility to tackle such heterogeneity. The first finding that suggested patent citations to be correlated with the value of innovations (Trajtenberg (1990)) used R&D output – measured by consumer surplus gain from development and diffusion of CT (Computed Tomography) scanners – as a proxy for the value of patents. Citation weighted patent counts were found to be more closely related to this output measure than un-weighted patent counts. These initial findings kick-started further work aimed at learning the exact role of citations among other patent characteristics in determining the value of patents. Hall, Jaffe and Trajtenberg (2001) demonstrated that the citation weighted patent counts are highly correlated with the financial market valuation (stock market price) of the firms that own patents. Lanjouw and Schankerman (2004) explored the use of other additional characteristics, namely the number of claims and family size, and demonstrated that using multiple indicators substantially reduces the measured variance in patent quality.

All of these studies rely on a proxy for the measure of the value of patents in order to attempt linking them to other known patent characteristics, such as changes in prices and attributes of CT scanners in the market to measure product innovation (Trajtenberg (1990)), and the stock market price of a firm for reflecting the economic value of innovations held by the firm (Hall, Jaffe and Trajtenberg (2001)). Unfortunately, such measures are often weak or inaccurate proxies for the value of patent portfolios, since a product's or a firm's value is determined by several other assets such as products, investments and capital assets etc. Using such proxies – which can only be proxies for the *aggregate* value of patent portfolios in a firm or a product area – also obscures the actual value of *individual* patents. Studies at product level or cross-firm studies do not link the number of citations for an *individual* patent to the value of the same *individual* patent.

Another problem in this type of aggregate data analysis comes from aggregating together various types of industries. Patent characteristics vary significantly across different technologies. For example, Alcacer, Gittelman and Sampat (2008) describe the determinants of patent citations in detail and demonstrate that the incentives on providing citations vary greatly by the innovation area. Indeed an aggregation over different industries may explain the varying and often conflicting results in past studies exploring the determinants of economic value of patents – for example Lerner (1994) found that 'broad' patents[2] are more valuable (litigated more often) for the biotechnology industry, Lanjouw and Schankerman (2001) found that 'narrower' patents are more valuable for mechanical and chemical industry[3].

Due to all these concerns with existing literature on the role of patent characteristics in determining the value of patents, Intellectual Property (IP) strategists and practitioners still struggle to define a good procedure for weighting the patent counts appropriately, or identify valuable patents from a large pool. It is rarely known what indicators available in the patent data determine the value of a patent, and to what degree.

In this study, I address both the need to link the potential indicators identifying the value of patents to *individual* patents, as well as the need to focus on one technology area to remove the heterogeneity in number of citations. I analyze data consisting of a group of firms in one industry that expended significant effort to rate their patents for acquisitions, sales, and other purposes. As typical practice in the industry, firms employ a multidisciplinary set of subject matter experts to evaluate patents once they have been granted or are close to granting, for the purposes of finding valuable patents. These patent values are more than mere opinions of subject matter experts and carry an economic meaning, as the market share of products that may infringe on a given patent are detectable (detailed explanation in Section 2.2). In the absence of data revealing the exact dollar values tied to most patents[4], such patent valuation ratings are the closest estimate of the poten-

[2]The definition of broad patents is the number of 4-digit International Patent Classification (IPC) code(s) assigned by the patent office for identifying the technology area to with the patent belongs. It is standard practice to assign more than one IPC code to a single patent.

[3]Lanjouw and Schankerman (2001) also found that the number of citations received by a patent (forward citations) and number of claims help towards identifying a more valuable (litigated) patent, while the number of citations included in a patent to older patents (backward citations) do not. In contrast, Allison, Lemley, Moore and Trunkey (2003) found that claims, forward as well as received citations, as well as how long patents took to be granted help towards determining their potential value. Finally, Gambardella, Harhoff and Verspagen (2008) discuss how the overall impact of all such patent indicators towards identifying patent value is small, when controlling for country and industry specific fixed effects.

[4]Most of the licensing agreements among firms are not revealed to the public, and therefore

tial economic value of patents. Focusing on specific industries or technology areas also removes an important source of heterogeneity in the patent characteristics in the first place.

In order to link these individual patent values with indicators estimating their value, I adopt a two-step estimation strategy. In the first step, I start by addressing the truncating problem in citation data, i.e., the fact that we observe the number of citations only until the time of observation, and therefore older patents would have received more number of citations than newer patents by definition. A predictive model is employed for predicting total number of citations that would be received by a patent in its lifetime. Once the citation count is corrected, the second step moves on to estimating the marginal value of each patent characteristic in predicting the likelihood of a patent being of some economic value.

The data illustrates that citations received by patents (a.k.a. forward citations) are the single biggest factor in predicting the economic value of patents. Other factors, such as citations made by a patent (a.k.a. backward citations), number of claims, family size, and office actions, do not carry significant predictive power – some of which have been found to carry predictive power in past studies with aggregate analyses across firms and technology areas. I test the robustness of this result by applying different specifications of the model predicting the total number of lifetime citations, and the results do not seem to be sensitive to the specific model specification. The contribution of this study is a step in the direction towards resolving the uncertain art of patent valuation, all the more important in today's highly litigious technology landscape, where high-profile patent portfolio acquisitions[5] have become commonplace.

This chapter is organized as follows: In Section 2.2, I describe the basic

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the estimates of licensing revenues generated by patents are typically not observed. If licensing agreements are unsuccessful, the involved parties may end up in a litigation dispute. Patent litigation data has been used in the past to identify valuable patents (Lanjouw and Schankerman (2001), Allison, Lemley, Moore and Trunkey (2003)). However, these studies themselves explain the limitations of using only litigated patents as valuable patents, since the most valuable patents arguably seamlessly result in a licensing agreement and only the 'second best' result in a dispute in the form of litigation.

[5]Among the recent acquisitions, the famous include Apple and partners' acquisition of Nortel's portfolio for $4.5 billion and Google's acquisition of Motorola Mobility for $12.5 billion, largely motivated by Motorola's ˜17,000 patents (CNN Money, August 15, 2011).

methods of evaluation of patents, and how they relate to the potential economic value indicated by each patent. In Section 2.3, I briefly describe the institutional background at the USPTO and the process by which publicly available patent characteristics that are explored in this study are generated. Here, I explore why each of these patent characteristics may or may not be an indicator towards the value of patents. Section 2.4 includes the description of the data set used in this study. In Section 2.5, I describe the two-step estimation strategy adopted for exploring the indicators for estimating the value of patents. Section 2.6 explores the relationship between patent valuation ratings and the timing of the received citations, and Section 2.7 concludes.

2.2 Private value of patents

At the outset it may help to explain what is meant by the 'value of patents' in this study. First, the term refers to the value of the patent and not the invention it protects. For example, many valuable inventions were never patented or were covered by ineffective patents, while many narrow and specific inventions led to valuable patents. Second, the term refers to the private economic value to the owner of the patent, rather than the patent's direct contribution to social welfare.

The keynote of the data set used in this study is a valuation rating assigned to each patent based on its potential economic value determined by the likelihood of products infringing on the patent, and the size of the product market. A typical practice in the industry is to employ a set of subject matter experts, usually comprising of technical as well as legal experts, to review patent records and assign them a valuation rating based on their potential to be used for licensing or litigation purposes[6]. The value of patents are represented by the valuation rating assigned to the individual patents on a scale of three: high, medium, or low. Based on interviews with law firms and consultants performing such evaluations in

[6]The ultimate economic goal of a patent to its owner is to generate licensing revenues (or royalties), by licensing the technology covered by the patent to products that use the invention protected by the patent. If the potential licensee refuses to pay the demanded royalty, the licensor may threaten to sue the licensee via a litigation or an antitrust case.

the industry, we will assume that any patent with medium or higher is considered potentially worthy for use in licensing negotiations or litigation purposes. The patents with high valuation ratings are the rare super-star game changing patents. Further, we will assume that any patent with a low valuation rating is considered unworthy of use in a licensing negotiation.

These patent valuations are more than mere opinions of subject matter experts, and carry an economic meaning due to the nature of the process involved in determining these valuations. For the ICT (Information and Communication Technology) area, some products must comply with internationally defined technical specifications called 'standards', published by the relevant standards organization[7], such as IEEE (Institute of Electrical and Electronics Engineers), IETF (Internet Engineering Task Force), or ITU (International Telecommunications Union). Some patents in the ICT area can be mapped to technologies that can be identified as included in published standards. Thus, the potential value of a patent can be determined based on whether it maps to an essential feature in a published standard, and if so, the market share of the product(s) that must comply with the standard. Other patents in the ICT area can be identified based on commonly used features in products, such as software features, user interface features, or even designs, and again the market share of the product(s) that may infringe on these patents determine the potential economic value of the patent.

The process of assigning patent valuation ratings by subject matter experts is based on determining whether the patent claims cover a feature required by a standard or a feature implemented by existing products, as well as the legal jurisdiction of the products' domain. For example, a patent that maps to products made, used or sold in U.S., Japan and China receives a higher valuation than a patent that maps to products that are only made, used or sold in China. The valuations are based on reviews carried out after the patent is granted, or close to granting, in order to be estimated with significant certainty of claims that are ultimately granted at or towards the end of the prosecution process, as well as more knowledge about the actual technology evolution since the filing date. Thus,

[7]A standards organization is a collaboration between groups of associations, known as the Organizational Partners, in order to define a globally applicable specification.

the patent valuation ratings are the closest estimate of the economic value realized by individual patents, in the absence of true dollar amounts of transactions related to individual patents.

2.3 Institutional background and patent characteristics

A patent by definition is a temporary legal monopoly issued to inventors for the commercial use of an innovation. In the U.S., patents are issued by the USPTO, a part of the department of commerce.

To get a U.S. patent, the inventor(s) file an application with the USPTO and pay a corresponding filing fee. A USPTO examiner then determines whether the innovation meets the standards of novelty and non-obviousness required by the U.S. patent statute in order to be patentable, by comparing the innovation covered by the application to 'prior art' (a legal phrase that covers everything known before the time of the patent application). The legal scope of a patent's coverage is described in its claims. If the examiner concludes that the claims cannot be granted, the applicant has the opportunity to redraft the claims, making them more restrictive, thereby distinguishing them from the prior art. Thus, the process of patent examination is largely one of negotiation between the examiner and the applicant. In principle, the granting rate of patent applications is fairly high, indeed, the standard of novelty and utility imposed on the granting is argued to be not very high (Griliches (1984)). Typically, the negotiation process, also known as 'patent prosecution phase', at the end of which the patent is granted takes 2-5 years in the US. During this phase, each correspondence between the applicant and the examiner is called an office action.

The date a U.S. patent application is filed with the USPTO is termed as its filing date. By law[8], the patent application is published and made publicly available 18 months after its filing date, termed as its 'publication date'. This is

[8]Prior to November 2000, the patent application was made publicly availably only after grant, and thus the publication and grant dates coincided.

when a patent application becomes available for being cited by other applications. Finally, the patent is granted on its 'grant date'. A patent expires 20 years from its filing date. During fixed periods throughout the patent's lifetime, an annuity fee needs to the paid by the patent holder to the PTO, to keep the patent alive.

Each patent contains highly detailed information on the innovation in the specification and the claims, the technological area to which it belongs (in the form of International Patent Classification (IPC) code(s) assigned by WIPO (World IP Organization)), the inventors (their name and geographical location), the assignee (typically a firm, organization, or university the inventor is associated with), and citations to previous patents or other scientific literature. These publicly available fields allow researchers to create potential indicators of the quality of individual patents. Along with this, other useful patent characteristics can be inferred, such as the number of countries the patent has been filed in, and the prosecution length (the time it took for the patent to be examined by the patent examiner before the final decision) of the patent. I describe the characteristics that can be used as indicators for the value of patents below:

1. **Patent citations**: Prior art in the form of citations play a crucial role in the process of negotiation between the patent applicant and the examiner, and therefore in determining the scope of the patent claims (a.k.a. property rights) that are ultimately awarded to a patent. In this regard, patent citations are very different from bibliographic citations, as they carry a strong legal significance.

   The citations listed in a patent arise from two sources – the applicant and the examiner. In the US, patent applicants have a "duty of candor" by law, to disclose any prior art citations to the patentability of an invention. The ultimate responsibility to add relevant citations rests on the patent examiner. However, the incentives faced by either for disclosing the most complete prior art are complex.

   If an applicant knowingly fails to disclose relevant prior art, s/he risks being accused of "inequitable conduct" defense in court by the potential accused infringer of the patent, thus rendering the patent invalid. Thus, stronger prior art searching and a longer list of claims helps towards ensuring an enforceable patent with higher likelihood. On the other hand, applicants are not legally required to search prior art, and may receive broader claims if the examiner fails to uncover prior art material to patentability. In the U.S., a strong presumption of validity enjoyed by patents, in addition to the high bar set on the level of proof required to prove inequitable conduct, provides an incentive to the applicants for not searching for and disclosing complete prior art to the USPTO.

After the applicants disclose their list of citations, the examiners at the USPTO further conduct their own prior art searches, based on which they may respond to applicants during the examination to modify their claims. However, examiners are not the subject matter experts in the specific technological area covered by patents, and there is enough evidence to suggest that the examiner search is limited by strict time deadlines, only made worse in the recent years (Thomas (2001), Cockburn et al. (2003)).

Thus, it is not immediately clear whether a higher number of citations *made* by a patent – **backward citations** – would contribute in favor of, or against, the potential value of a patent. On the other hand, a higher number of citations *received* by a patent – **forward citations** – may indicate the social impact of that patent on future inventions, which can be measured by the number of inventions that build upon this patent. However, it is not clear that higher social impact may also translate into the potential economic value of a patent to its holder.

2. **Number of claims**: Each patent comprises a set of claims that represent the legal boundary of the property rights granted to the applicant. In order to determine whether an accused defendant truly infringes a patent, the claims of the patent are compared against the defendant's product. Thus, the patent applicant has an incentive to claim as much as possible, while the examiner may restrict the scope, as well as the number of claims. It should be noted that there is a cost associated with filing more claims for the applicant. The minimum USPTO fee covers twenty claims per patent (three independent

and seventeen dependent claims), with an additional fee required per claim. In addition, the drafting and prosecution attorneys – typically hired by the applicant firm – usually charge a substantial per claim fee.

Therefore, a higher number of claims may be a result of a principal-agent problem, where patent attorneys file more claims (e.g.: a repetitive set of method, apparatus and system claims for the same concept) for jacking up their fee, or they may represent a higher effort expended towards receiving broader claims for a more valuable invention.

3. **Number of office actions**: During the prosecution phase, the patent examiner at the USPTO responds to the applicant's request by issuing an office action – a document citing prior art and explaining why the examiner has allowed, or approved, the applicant's claims, and/or rejected the claims. An office action may be 'final' or 'non-final'. In a non-final office action, the applicant is entitled to reply and request reconsideration or further examination, with or without making an amendment to the claims. In a final office action, the applicant may appeal rejection of claims or file an amendment that complies with the requirements set forth in the office action. A typical patent may receive one to five office actions before reaching a final decision.

   The number of office actions before a patent is granted is not publicly available in a handy format. Past studies have used a related variable – a coarse measure of the prosecution length of each patent, as the difference between the filing and the grant date. However, our data set contains the exact number of office actions incurred.

   The more times the patent applicant returns to the examiner to argue the case, the longer the prosecution will take and incur a higher number of office actions – or back and forth negotiations between the examiner and the applicant. However, for larger firms with a flat policy for all patents outsourcing the prosecution, a higher number of office actions may simply be a proxy for weaker (narrower) patent claims at the end of the prosecution.

4. **Family size**: Many patents belong to a patent family, i.e., originate from a

single application. The size of the patent family captures two things: (i) the number of countries in which a patentee sought protection, or the geographic scope of the patent; and (ii) multiple patents issued in a single jurisdiction (e.g. US) in the form of continuations or divisionals, spawning out of the same original application, refereed to as the 'parent'.

Intuitively, the metric capturing the geographic scope should reflect a patent's value, as firms will seek protection of the most valuable patents in the largest number of countries. However, patents are a temporary legal monopoly on **products**, and therefore firms' strategies on where to file patents almost always depend upon the complex function of the expected revenue from a geographical area for its products, enforceability (or strength of the legal system) in a geographical area, budget constraints, and other factors along with the patents' potential quality. The metric capturing the number of new patents (in the form of continuations or divisionals) spawned out of the original application may also imply a more valuable patent worth filing a continuation on; and on the other hand may imply a weaker parent patent that led to the filing of a continuation during the end of the prosecution, to draft a new and related set of claims (often the easiest thing to do for a prosecution attorney).

Thus, for each characteristic, it is not clear ex-ante whether there is any conclusive relationship with the patent value and if there is, what direction of that relationship may be.

2.4 Description of the data

The data set spans from patents filed between 1985 and 2011 for a group of firms specializing in the ICT area. The data set only includes all the U.S. utility *patents and applications* (informally called *patent records* throughout the rest of this chapter), with the total count exceeding 10,000. During this period, the patent records that cite any of thesepatent records[9] are also included, totaling over 150,000 cited and citing patent records in the data set. All together, this dataset therefore generates a large enough sample for the ICT industry.

Corresponding to each cited patent record, we observe the patent characteristics described in Section 2.3, namely, the number of citations, number of claims, family size of the patent record, and the number of office actions received by a granted patent during prosecution[10]. The area of technology covered by a patent is recorded in the form of IPC codes designated by the patent office. A large majority of patents in the dataset fall under the same 3-digit IPC code, and thirteen 4-digit IPC codes. The valuation of high, medium, or low assigned to each patent record, that serves as an indicator for the corresponding potential economic value, is only provided for research purposes for a subset of randomly selected patent records in the data.

Table 2.1 reports the summary statistics for the data on observed patent characteristics based on the patent valuations. Consistent with previous findings in the literature on the overall distribution of the value of patents (Schankerman and Pakes (1986)), the intrinsic private value of patents for this sample also exhibits a highly skewed pattern: with high value patents being relatively small in number. Although the means for all the patent characteristics move in a common direction, with higher values for highly rated patents, not much can be inferred from the table due to large standard errors around the means. Therefore, I explore the distribution of patent characteristics based on their patent valuation ratings, as the large standard errors are driven by highly skewed distribution in the underlying characteristics as well.

Figure 2.1 shows the empirical cumulative distribution function of the logarithm of forward and backward citations for highly valued patent records versus those with a low value patent records. As can be observed, the distribution of high-rated patents stochastically dominates the low-rated patents for both forward and

[9]The list of forward citations includes citations coming from U.S. as well as foreign (non U.S.) patent records

[10]The total number of office actions are included in the data set only for the granted patents, as they would be incomplete and meaningless for patent applications.

backward citations. A similar trend for the number of claims is observed as well. This suggests that patent valuation ratings seem to be correlated with the patent characteristics.

Before starting to explore the various patent characteristics, a crucial problem with citations data must be addressed, namely the truncation of the forward citations due to number of years for which we observe the citations. A patent can be cited at any time after it is published. For the observed forward citations, I use the publication dates to compute their lag distribution, by computing the difference between the publication date of citing patents versus that of the cited patent[11].

Figure 2.2 plots the average citation frequency[12] as a function of citation lag, as observed in our data set. This figure shows that on average, the number of received citations peaks around 5-7 years from the date of publishing, before starting to drop with a steady decay. This suggests that although the majority of citations happen in the first few years of a patent's life, there may be a long tail of citations that can occur well into its future lifetime.

Because the citations data only go until 2011, I only observe the first few years of citations for recently published patents (for example for patents published in 2006, our citations abruptly stop at lag 5). In order to allow published patent applications to receive enough time to be cited, I truncate the data set until the publication date of January 2009 for a less noisy prediction of the total number of citations, thus allowing at least 2.5 years for receiving citations. This leaves us with 8,613 unique cited patent records, which are used for estimating the shape of the citation lag distribution, i.e., the number of citations received in each year after a patent is published. After estimating the citation lag distribution I can predict the total number of citations that will be received by a patent in its lifetime. Section 2.5.1 describes the estimation strategy and results for prediction of lifetime forward citations received by a patent.

[11] This is because a patent application becomes publicly available for being cited as soon as it is published.

[12] The average citation frequency is obtained by dividing the number of received citations per patent by the total number of patents in the cited year patent cohort.

From the 8,613 records, $\sim$3000 have patent valuation ratings assigned to them. These observations are used for exploring the impact of patent characteristics on patent valuation, after correcting for the citation count. Section 2.5.2 describes the results for estimating the impact of patent characteristics on the potential economic value of patents.

2.5 Estimation methodology

In order to explore which patent factors can provide reliable estimates for the value of patents, I follow a two-step estimation approach:

1. Predict the total number of forward citations received over a patents lifetime.

2. Estimate the impact of patent factors: Number of forward (predicted) and backward citations, number of claims, family size and number of office actions on the corresponding patent valuation (serving as a proxy for the economic value) of the patent record.

2.5.1 Step 1: Predicting the total number of citations

In order to predict the total number of citations that will be received by a patent in its lifetime, I start by estimating the shape of the citation lag distribution from the data, i.e., the number of (forward) citations received in each year after a patent is published.

The empirical average citation lag distribution, as shown in Figure 2.2, is similar to the pattern observed in previous literature (Jaffe and Trajtenberg (1996)). The shape of this distribution lends itself well to the formulation of patent citations following a double exponential function that can be interpreted as a mixture of diffusion and obsolescence functions. The first part, where the citations slowly increase, relates to a slow technology diffusion process where other inventions gradually learn about this patent and start citing it. The second part demonstrates a gradual fade away of the technology, as it becomes older and obsolete. A double exponential formulation allows the estimation of a technology diffusion rate during the beginning of a patent's life, and an obsolescence rate afterwards.

Figure 2.3 displays the plot of the average citation lag distribution for different 'cohorts' of patents (defined by the year of publication of the patent). As the figure illustrates, the shape of the distribution function is similar across the years shown, although for the more recent years only a part of the distribution is observed[13].

The empirical model that I follow for analyzing the process underlying the generation of citations and identifying the age distribution is based on the widely discussed specification in the literature from Jaffe and Trajtenberg (1996) and in Hall, Jaffe, and Trajtenberg (2001), which adapt the original formulation proposed by Caballero and Jaffe (1993).

The citation probability is modeled as a multiplicative function of cited-year t effects, citing-year T effects, and citation lag $s = T - t$, as follows:

$$p_{t,t+s} = \alpha_t \alpha_{t+s} \, f_s,$$

where f_s is a function describing how the likelihood that a patent published at time t is cited by a patent published at time T depends on the lag s.

As discussed above, the function f_s is characterized as a double exponential lag profile[14]:

$$f_s = e^{-\beta_1 s}\big(1 - e^{-\beta_2 s}\big),$$

where the parameters β_1 and β_2 represent the rate of obsolescence and of diffusion of technology, respectively. By adding an error term $\varepsilon_{t,t+s}$, we obtain the following estimation equation:

$$p_{t,t+s} = \frac{c_{t,t+s}}{n_t} = \alpha_t + \alpha_{t+s} + \log\left(e^{-\beta_1 s}\big(1 - e^{-\beta_2 s}\big)\right) + \varepsilon_{t,t+s}, \tag{2.1}$$

where $c_{t,t+s}$ denotes the total number of citations received by patents published in year t from patents published in year $t + s$ and n_t denotes the number of patents

[13] Only four years are displayed in the figure for the sake of brevity, however, the distribution of citations appears to be similar across all years.

[14] The same approach has been used in the previous literature by Jaffe and Trajtenberg (1996), Hall, Jaffe and Trajtenberg (2001), Bacchiocchi and Montobbio (2004), Branstetter and Ogura (2005), and Adams, Clemmons and Stephan (2006).

published in year t. The parameters for this equation can be estimated using non-linear least-squares estimation.

The model in (2.1) was fit to 133 observations from citation data aggregated by publication year (1994-2008) and citation year (1995-2011). Each observation consists of the ratio of the number of citations with a given lag and the number of published patents in a given year. In principle, it should be possible to estimate the citing year, cited year, and lag together in a single equation. However, I found that estimation was difficult with a full set of unconstrained cited year and citing year effects, as the non-linear fit does not converge with a large set of variables. Because it is believed that the true 'fertility' of invention changes only slowly, I grouped the cited years and estimated separate α_t coefficients for five-year intervals. The citing year α_{t+s} effects are allowed to vary every year.

The results in Table 2.2 show that each of the cited and citing year effects are significant. There is a steady upward trend displayed by α_{t+s} and a steady downward trend displayed by α_t effects, consistent with findings in the previous literature (Jaffe and Trajtenberg (1996)). The increasing value of citing year effects are explained by the well-known institutional phenomenon of increasing propensity to cite over time, due to easier access to computerized patent data. By contrast, for the decline in cited year effects, the past literature conjectures a decline in fertility of patents over time. Since our data is technology specific, this decline can be explained as being due to the nature of the technology. During the inception of a new technology, inventions tend to be fundamental in nature and evolve to incremental improvements over time.

The plot of the estimated obsolescence and diffusion parameters, juxtaposed over the average empirical citation frequency across all years is shown in Figure 2.4. The fitted lag distribution approximately follows the average citation frequency curve. As I follow the fitted lag distribution, the rising slope of the curve corresponds with the technology diffusion factor, and the decaying slope corresponds to the technology obsolescence factor. Comparing with findings in the previous literature (Jaffe and Trajtenberg (1996)), the obsolescence factor for our data set (compared to $\beta_1 = 0.15$) is lower than the aggregate rate over all technological fields. This may be due to the technological nature of the specific technology area, which display a long time for evolving and subsequent obsoleting[15]. The diffusion factor ($\beta_2 = 0.73$) is higher as well, representing a relatively faster progress in this technology area[16].

The predicted number of missing citations at lag $t+s$ for a patent issued at time t when we do not observe citations beyond time $t + s_{\max}$ is the following:

$$p_{t,t+s} = f_s \, \frac{\sum_{j=0}^{s_{\max}} c_{t,t+j}}{\sum_{j=0}^{s_{\max}} f_j}$$

The first term on the right hand side represents the predicted lag distribution, while the second term indicates an adjustment of the predicted citations based on the observed citation intensity. For example, a patent published in 2006 that has already received 10 citations is more citation intensive than a patent published in 1996 with 11 citations received thus far, and thus will likely receive a higher number of lifetime citations. To derive the estimated total citations for any patent, I sum the observed citations from the observed years and the predicted citations based on the above methodology for the unobserved years. Totals based on this methodology are used to construct the predicted lifetime citation counts used in the Step 2 regression.

In this empirical model for estimating the total citations, I have made a specific assumption on the functional form f_s (the dependence of the citation probability on the citation lag s). The results presented in Section 2.5.2 may be sensitive to this assumption. In order to test the robustness of the results presented in Section 2.5.2 on the choice of the function f_s, I also explore the use of an alternative specification in Appendix A.

[15] As an example, definition of the global second generation cellular system called GSM (Global System for Mobile Communications) standard began in 1982, with phase-I completed in 1990, followed by several subsequent revisions. In 2010, GSM and standards evolved on top of GSM are still in use by more than 75% of cellular subscribers around the world.

[16] Indeed, the high tech industry has seen a relentless progress towards faster and more scalable standards in the last few decades

2.5.2 Step 2: Estimating the impact of patent factors on patent values

Ordered probit is used for relating the patent valuation ratings to various patent characteristics, as the valuation ratings have a natural ordinal interpretation, represented categorically on a scale of low, medium, and high.

I first start by using the number of observed forward citations as a regressor, without using the results for predicted forward citations derived in Step 1. This is a simple first order regression, without addressing the truncation of citations. Table 2.3 represents the ordered probit regressions relating the patent valuation ratings of all the patent records to the following regressors: the number of (observed) forward citations, backward citations, number of claims, and family size. Because the total number of office actions are only observed for granted patents, the results from adding office actions as a regressor are reported in a separate column. The table presents the parameter estimates and the implied marginal effect of each variable on the private value of patent. The marginal effects can be interpreted at the sample means, and the sign effects of the lowest and highest valuations are completely determined by sign of the marginal effect coefficient.

The results confirm that the likelihood of a patent receiving a high valuation rises with the number of forward citations. Column 1 shows the parameter estimates for the ordered probit, and only the parameters for log of forward citations and log of number of claims are statistically significant in the 99% confidence interval. Because in an ordered probit model the signs of the 'interior' marginal effects are not completely determined by the sign of the coefficient, the marginal effect on the lowest and highest valuation are displayed in columns 2 and 3. For both the forward citations and claim count, the signs of their marginal effects on the lowest rating (-0.007 and -0.017, respectively) and on the highest rating ($+0.004$ and $+0.009$, respectively), indicate that the likelihood of observing a higher patent rating increases as the number of forward citations and claim count go up. The likelihood ratio chi-square of 94.40 with a p-value of 0.000 indicates that the proposed model is statistically significant.

The δ_j are the threshold parameters, estimated by the data to help match the probabilities associated with each discrete outcome. For example, δ_1 represents the threshold of the weighted sum of regressors below which the corresponding patent valuation is estimated to be low, and δ_4 represents the threshold above which the corresponding patent valuation is estimated to be high.

Column 4 shows the parameter estimates for the ordered probit for granted patents only, i.e., patent records for which the final office action has been received and claims have been granted by the patent office. I find that the effect of number of claims drops significantly, while the effect of the number of forward citations still holds, as compared to the parameter estimates for all patent records in column 1. The number of observations is lower and the likelihood ratio chi-square drops to 26.27, but the model remains statistically significant as the p-value remains at 0.000. The marginal effect of the forward citations on the lowest ratings in column 5 (-0.005) and the highest ratings in column 6 ($+0.003$) displays a sign that indicates the likelihood of observing a higher patent rating increases as the number of forward citations increase.

Column 7 shows the parameter estimates for the ordered probit for granted patents only, with an additional control variable reflecting the total number of office actions per granted patent. The parameter estimates in column 7 are not very different from those in column 4 obtained without the additional control variable. The results confirm with columns 4-6, in that the effect of number of claims is wiped out, while the effect of the number of forward citations remains unchanged. The marginal effect of the forward citations on the lowest ratings in column 8 and on the highest ratings in column 9 remain unchanged as well. The likelihood ratio chi-square is similar as well, at 26.50, and the model remains statistically significant as the p-value remains at 0.000.

Why does the significance of claim count disappear for granted patents? An explanation of this observation may be that a higher number of claims are a proxy for a higher effort expended by the drafting attorney, resulting in broader protection and thus a higher potential value of the patent. However, after the patent application reaches the end of prosecution after receiving the final office action(s), the claim amendments make those effects disappear. Therefore, a higher number of claims display a broader *potential* scope of a patent application, but once the definitive set of claims are granted, the scope of the patent is independent of the number of claims.

Moving on towards using the results for predicted forward citations derived in Step 2, Table 2.4 represents the ordered probit regressions similar to Table 2.3, except that the number of predicted lifetime forward citations is used instead of only using the observed citations. As expected, a better model fitting is observed in column 1 (likelihood ratio chi-square of 165), with lower standard errors around the forward citation coefficient, which jumps to 0.19 from the value of 0.09 from observed citations only[17]. The marginal effect of the predicted forward citations on the lowest ratings in column 2 (-0.014) and the highest ratings in column 3 ($+0.008$) is a marked increase from using the observed citations only (compared against columns 2 and 3 in Table 2.3). The marginal effect of claim count on the lowest and highest ratings also displays a sign that indicates that the likelihood of observing a higher patent valuation rating increases as the number of forward citations increase.

Columns 4-6 are results from the ordered probit for granted patents only. Similar to Table 2.3, column 4 again demonstrates that the effect of number of claims drops significantly while the effect of the number of forward citations still holds, as compared to the parameter estimates for all patent records in column 1. The number of observations is lower compared to column 1 and the likelihood ratio chi-square drops to 35.68, but the model remains statistically significant as the p-value remains at 0.000. The marginal effect of the forward citations on the lowest ratings in column 5 (-0.007) and the highest ratings in column 6 ($+0.005$) displays a sign that indicates that the likelihood of observing a higher patent rating increases as the number of forward citations increase.

Column 7-9 are results from the ordered probit for granted patents only, with an additional control variable reflecting the total number of office actions

[17]Since the independent variable representing the number of total predicted citations is measuring the sample variability (from step 1), the standard error of the coefficient on forward citations is not accurate, and needs to be fixed via bootstrapping. However, the small size of the standard error provides confidence that the significance of the coefficient is not impacted by this inaccuracy.

per granted patent. The parameter estimates in column 7 are no different from the result without the additional control in column 4. The results confirm with columns 4-6, in that the effect of number of claims is wiped out, while the effect of the number of forward citations remains unchanged. The marginal effect of the forward citations on the lowest ratings in column 8 and on the highest ratings in column 9 remain unchanged as well. The likelihood ratio chi-square is similar as well at 36.15, and the model remains statistically significant as the p-value remains at 0.000.

Thus, it appears that forward citations do posses an explanatory power for the economic value of patents. Other characteristics, such as backward citations, office actions and family size do not serve as indicators of patent values. The number of claims do seem to contribute towards estimating the value of patents until they are granted and have completed the prosecution phase, however, the final claim count after receiving all the office actions does not carry any significance towards the value of patents.

2.6 Robustness check: citations before and after patent ratings

One concern with the estimation strategy in Section 2.5 could be the relationship between the citations and patent valuation ratings. If the subject matter experts are assigning the ratings by taking the number of observed citations into account, then a reverse causality confounds the results and renders the effect of citations on patent valuation ratings meaningless.

In this section, I check whether the patent valuation ratings are independent of incoming citations. I take advantage of the fact that we observe the date when the rating was assigned to a patent by the subject matter experts. Patent valuation ratings are typically assigned 4-5 years after the date of application, in order to be aligned with the date of grant. This is a rational and implementable firm strategy in light of the uncertain time it typically takes for a patent to be granted. Therefore it is possible to count the number of citations received before and received after the patent valuation rating is assigned.

There can be three possible scenarios:

(i) If the impact of citations received before the ratings is much *higher* on the ratings, than that of citations received after the ratings, there is a clear concern: that experts may be looking at the citations when assigning ratings to the patents.

(ii) If the impact of citations received before and after is equal, then the result is ambiguous, as citations before and after are heavily correlated with each other (the empirical correlation between the number of citations received before and after the ratings is 0.70).

(iii) If the impact of citations received before the ratings is much *lower* on the ratings, than that of citations received after the ratings, then it would appear that the experts do not take citations into account and that the citations follow the predictions of the experts.

Results of ordered probit relating the patent valuation ratings to observed citations before and after the ratings, while controlling for all the other patent characteristics, are presented in Table 2.5. The parameter estimates in column 1 indicate the effect of the citations received before the ratings on the patent rating themselves to be small (0.05) and statistically insignificant. At the same time, the coefficient for the citations received after ratings is much larger in magnitude (0.24) and statistically significant. The marginal effect of citations-before and citations-after on the lowest and highest patent ratings are reported in columns 2 and 3 respectively. The marginal effects of citations-before on the lowest rating (-0.003) and highest rating ($+0.002$) are much less marked than the marginal effects of citations-after on the lowest rating (-0.013) and highest rating ($+0.008$).

The results indicate the third scenario to be true for the data. The patent valuation ratings do not simply follow the observed forward citations to date, but rather they play the role of predictors for the future citations that a patent will receive in its lifetime. Therefore, the relationship between the forward citations received by a patent and its potential economic value is indeed real.

2.7 Conclusion

I employed a sample data set that observes an estimate of the economic value of individual patents for a specific technology area. This enables us to get a statistical picture of the relationship between the various observable characteristics of patents and their private values. The most important finding is that there is indeed a relationship between forward citations and the potential value of patents. Our estimates are also in line with previous literature, in the sense that the distribution of patent values is highly skewed.

However, adding yet to the conflicting results from past studies exploring determinants of economic value of patents, I find that forward citations are possibly the only factor that may have an impact on the value of patents. The number of backward citations, claim count, size of the patent family and intensity of the prosecution effort seem to have no impact on the value of patents. I posit that a variation in results from past studies may arise from aggregating together a wide variety of technology areas, as the values and importance of patent factors across each of these varies significantly. The specific technology area that I study displays that it obsoletes at a slower rate than the aggregate rate found in the previous literature, and this may explain a higher impact of forward citations on patent values. Given that a patent's economic value for the technology area of our study is determined based on the evolution of related technologies, the size of a patent's family and intensity of the prosecution effort do not carry any impact on the value of the patent.

This study finds that new and better explorations of determinants of the economic value of patents must rely on data at the individual patent level, and must focus on specific technology areas, for future research. The ability to associate observable characteristics of patents with their potential economic value can help towards developing patent valuation tools and enabling efficient intellectual property markets.

Chapter 2, in part is currently being prepared for submission for publication of the material. The dissertation author was the primary investigator and author of this material.

2.8 Appendix A: An alternative specification

In the empirical model that was followed to predict the unobserved lifetime citation counts in Section 2.5.1, I made a specific assumption on the functional dependency f_s of the citation probability on the lag s between the cited patent and the citing patents. To test the robustness of the results presented in Section 2.5.2 on the choice of the function f_s, I propose an alternative specification based on the following functional form:

$$f_s = d_0 \; s^{d_1} \; e^{-d_2 s}. \tag{2.2}$$

In the above expression the parameter d_1 determines the rate of diffusion of technology while d_2 determines the rate of obsolescence. Observe that the rate of growth of the probability is polynomial in s with exponent d_1 instead of being exponential as in the double exponential lag profile function discussed in Section 2.5.1. This functional form is suggested because it is the most natural choice of fit for the citation lag distribution displayed by our data, as shown in Figure 2. In addition to a polynomial diffusion function for fitting the rise in the number of received citation with time, an exponentially decaying function is used for fitting the decay after the peak of received citations is reached. A purely polynomial functional form would result in difficulty in constraining the tail of the distribution to decay to zero or above as time tends to the patent's expiration date.

Table 2.6 reports the results of the non-linear fitting of the observed citations with the model based on (2.2). Comparing these results to those in Table 2.2, I notice that modified functional form produces an improvement in the R-squared and a reduction in the standard estimation error.

Table 2.7 reports the results from the second step regression using ordered probit, with the number of total predicted lifetime forward citations obtained from this alternative specification as a regressor. The results are again consistent with those obtained by using only the observed citations, or by using the predicted lifetime citations from the model in Section 2.5.1.

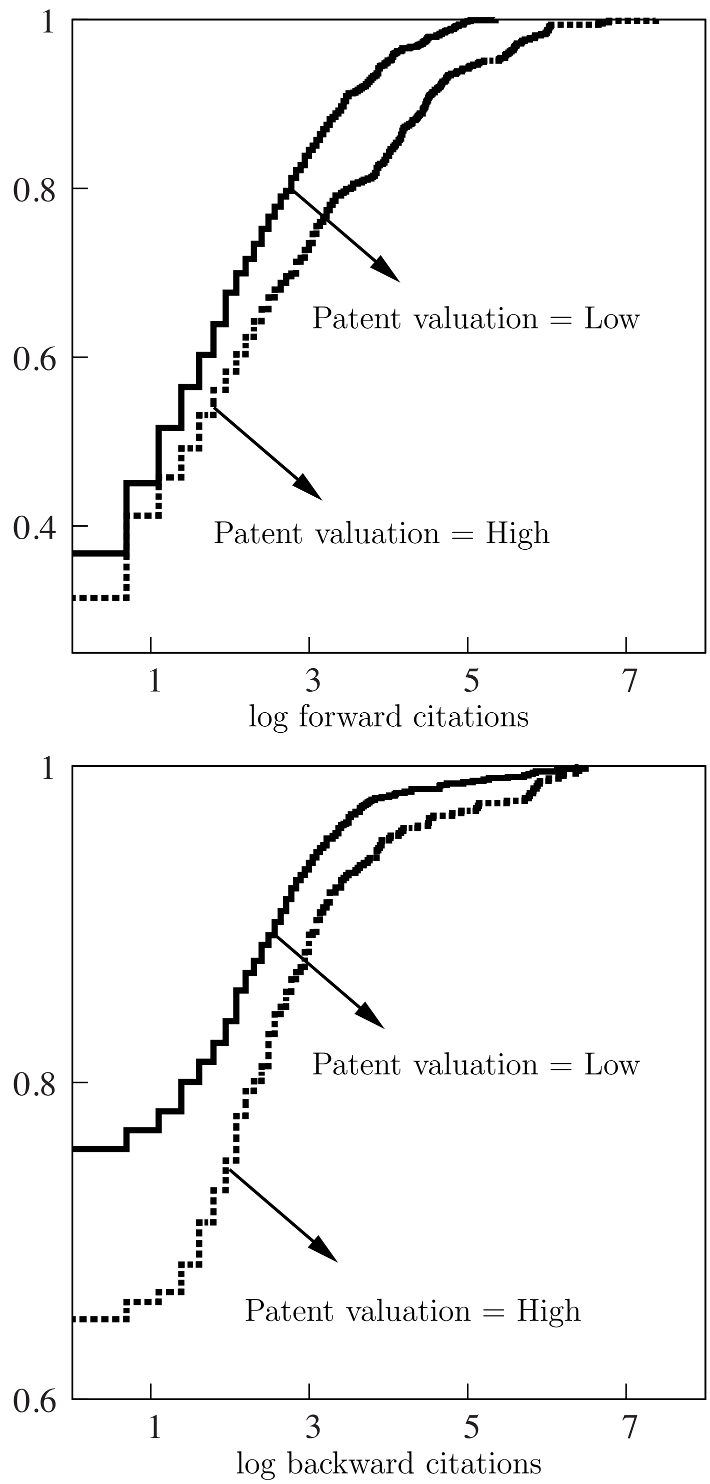

Figure 2.1: Empirical cdf of the log of forward/backward citations.

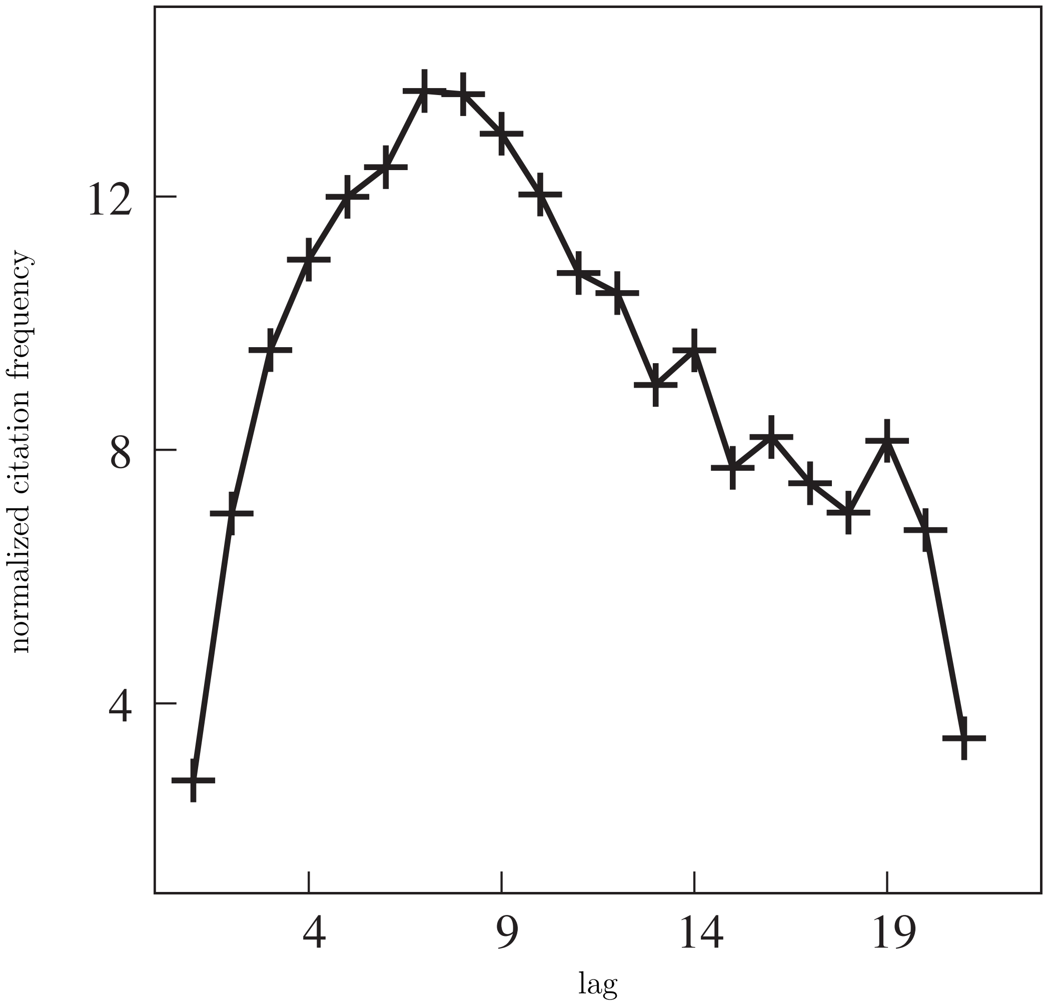

Figure 2.2: Normalized citation frequency vs lag.

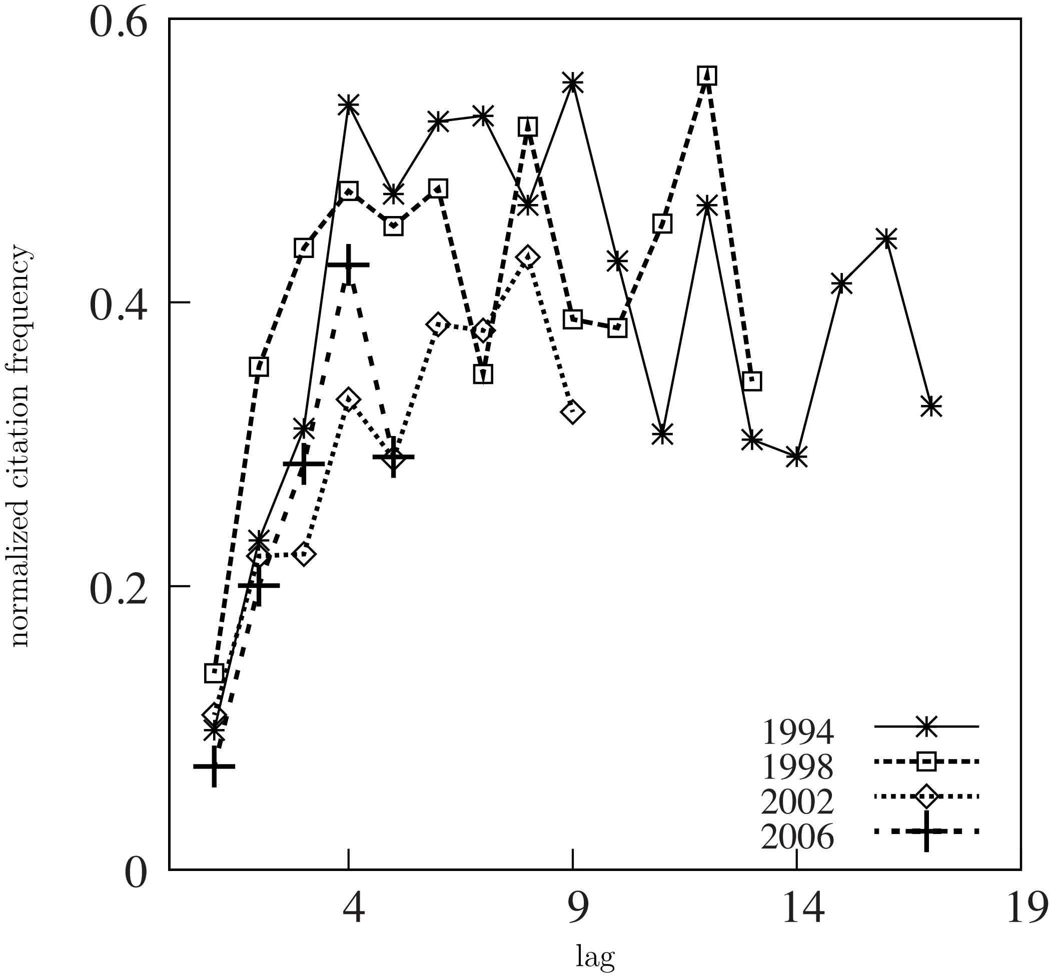

Figure 2.3: Normalized citation frequency vs lag for different years.

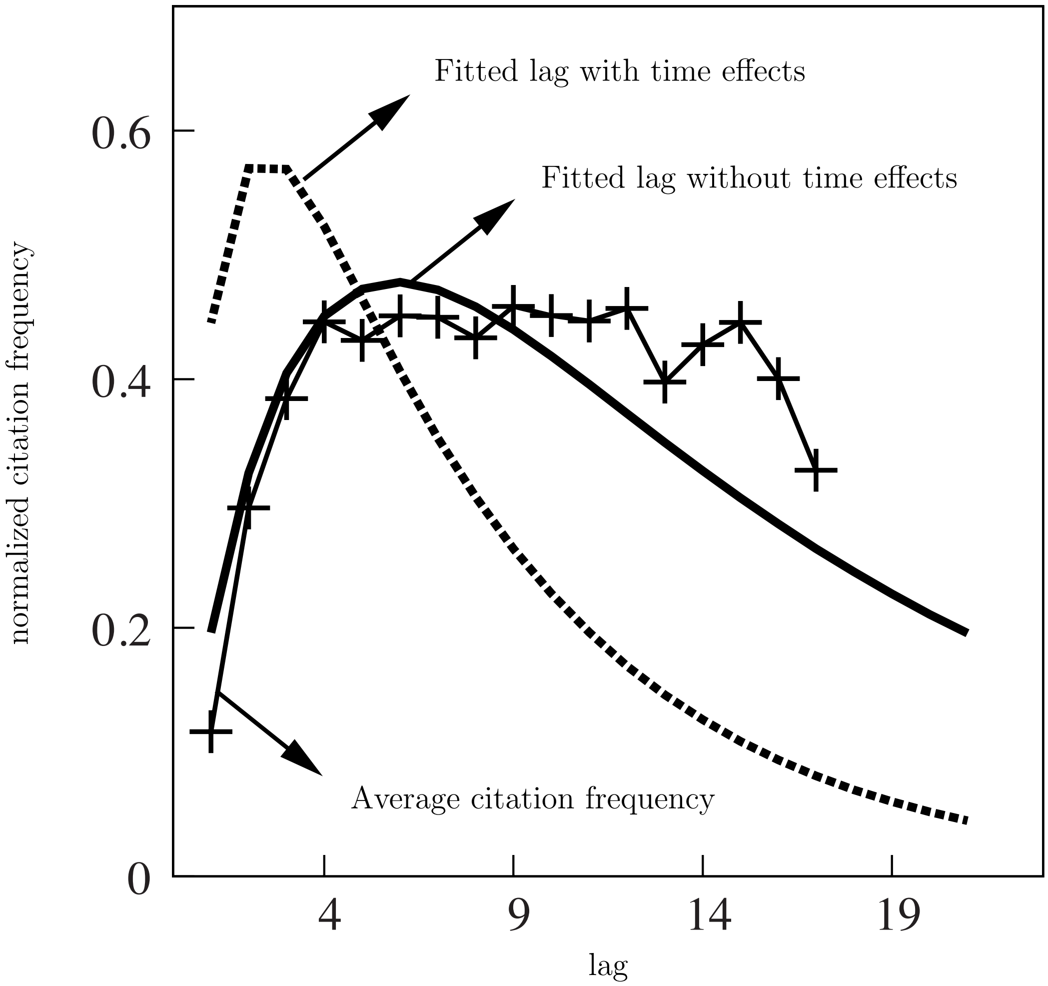

Figure 2.4: Normalized citation frequency vs lag.

Table 2.1: Summary table of patent valuations

	Patent valuation statistics			
Mean	Total	High	Medium	Low
Forward citations	18.28 (54.07)	36.19 (106.90)	11.26 (22.15)	13.65 (25.72)
Backward citations	10.26 (44.19)	16.92 (66.44)	8.96 (42.46)	2.55 (5.91)
Total claims	25.20 (18.45)	34.98 (22.31)	23.40 (17.56)	15.05 (9.76)
Family size	8.52 (19.11)	10.05 (20.57)	7.90 (18.85)	4.58 (13.29)
Office actions	2.55 (1.92)	2.59 (1.84)	2.55 (1.99)	1.78 (0.95)

Standard deviation are in parentheses.

Table 2.2: Estimation of citation probability as in Section 2.5.1

	Coefficient	S.E.
Cited year effects		
1994–1997	2.159***	0.095
1998–2001	1.700***	0.078
2002–2005	0.952***	0.064
2006–2008	0.400***	0.021
Citing year effects		
1995	0.604***	0.123
1996	0.649***	0.127
1997	1.201***	0.127
1998	1.161***	0.125
1999	1.434***	0.096
2000	1.487***	0.095
2001	1.539***	0.093
2002	1.712***	0.091
2003	1.750***	0.074
2004	1.546***	0.073
2005	2.051***	0.071
2006	1.886***	0.070
2007	2.128***	0.062
2008	2.392***	0.062
2009	2.703***	0.063
2010	2.467***	0.054
Parameters		
β_1	0.148***	0.010
β_2	0.726***	0.093
R-squared	0.942	
S.E. of regression	0.1667	

133 Observations.

Table 2.3: Ordered probit estimation of patent valuations using observed citations

	Without office actions			Without office actions			With office actions		
	Parameters	Marginal Effects Low	Marginal Effects High	Parameters	Marginal Effects Low	Marginal Effects High	Parameters	Marginal Effects Low	Marginal Effects High
Log forward	0.204***	-0.014***	0.008***	0.122***	-0.005***	0.003**	0.123***	-0.005***	0.003**
citations[a]	(0.019)	(0.002)	(0.001)	(0.031)	(0.002)	(0.001)	(0.031)	(0.002)	(0.001)
Log backward	0.014	-0.001	0.001	0.012	-0.001	0.000	0.011	0.000	0.000
citations	(0.021)	(0.001)	(0.001)	(0.029)	(0.001)	(0.001)	(0.029)	(0.001)	(0.001)
Log number	0.161***	-0.011***	0.006***	0.108	-0.005	0.003	0.103	-0.004	0.003
of claims	(0.045)	(0.003)	(0.002)	(0.076)	(0.003)	(0.002)	(0.076)	(0.003)	(0.002)
Log family	-0.023	0.002	-0.001	0.006	0.000	0.000	0.006	0.000	0.000
Size	(0.031)	(0.002)	(0.001)	(0.048)	(0.002)	(0.001)	(0.048)	(0.002)	(0.001)
Log office							0.051	-0.002	0.001
actions							0.046	0.002	0.001
Observations	2930			1373			1373		
Log-likelihood	-3313			-1385			-1384		
LR χ^2 (p-value)	194.66 (0.000)			50.00 (0.000)			51.25 (0.000)		
Pseudo-R^2	0.028			0.018			0.018		

[a] Observed values only.
All regressions include yearly time dummy variable. Standard errors are in parentheses.

Table 2.4: Ordered probit estimation of patent valuations using total predicted citations

	Without office actions			Without office actions			With office actions		
	Parameters	Marginal Effects Low	Marginal Effects High	Parameters	Marginal Effects Low	Marginal Effects High	Parameters	Marginal Effects Low	Marginal Effects High
Log forward citations[a]	0.212***	-0.015***	0.008***	0.113***	-0.005***	0.003**	0.115***	-0.005***	0.003**
	(0.018)	(0.002)	(0.001)	(0.028)	(0.001)	(0.001)	(0.028)	(0.001)	(0.001)
Log backward citations	0.009	-0.001	0.000	0.009	0.000	0.000	0.007	0.000	0.000
	(0.021)	(0.001)	(0.001)	(0.029)	(0.001)	(0.001)	(0.030)	(0.001)	(0.001)
Log number of claims	0.150***	-0.010***	0.006**	0.103	-0.004	0.003	0.098	-0.004	0.002
	(0.045)	(0.003)	(0.002)	(0.076)	(0.003)	(0.002)	(0.076)	(0.003)	(0.002)
Log family Size	-0.019	0.001	-0.001	0.010	0.000	0.000	0.010	0.000	0.000
	(0.031)	(0.002)	(0.001)	(0.048)	(0.002)	(0.001)	(0.048)	(0.002)	(0.001)
Log office actions							0.056	-0.002	0.001
							(0.046)	(0.002)	(0.001)
Observations		2930			1373			1373	
Log-likelihood		-3305			-1385			-1384	
LR χ^2 (p-value)		210.26 (0.000)			50.20 (0.000)			51.68 (0.000)	
Pseudo-R^2		0.031			0.018			0.018	

[a] Including estimated values for the un-observed values.
All regressions include yearly time dummy variable. Standard errors are in parentheses.

Table 2.5: Ordered probit using before-rating and after-rating citations

	Without office actions		
	Parameters	Marginal Effects Low	Marginal Effects High
Log forward citations before	0.044 (0.062)	-0.003 (0.003)	0.002 (0.002)
Log forward citations after[(a)]	0.227*** (0.053)	-0.013*** (0.004)	0.008* (0.003)
Log backward citations	0.006 (0.045)	-0.001 (0.002)	0.001 (0.002)
Log number of claims	0.117 (0.114)	-0.005 (0.006)	0.003 (0.004)
Log family Size	-0.056 (0.073)	0.004 (0.004)	-0.002 (0.003)
Log office actions	0.076 (0.071)	-0.001 (0.001)	0.001 (0.001)
Thresholds			
δ_1	-3.538 (0.804)		
δ_2	-2.333 (0.800)		
δ_3	-0.386 (0.802)		
δ_4	0.753 (0.796)		
Observations		589	
Log-likelihood		-578	
LR χ^2 (p-value)		51.16 (0.000)	
Pseudo-R^2		0.042	

[(a)] Including only the observed values.
All regressions include yearly time dummy variable. Standard errors are in parentheses.

Table 2.6: Estimation of citation probability as in Appendix A

	Coefficient	S.E.
Cited year effects		
1994–1997	2.078***	0.085
1998–2001	1.634***	0.069
2000–2003	0.918***	0.057
2006–2008	0.400***	0.003
Citing year effects		
1995	0.604***	0.058
1996	0.761***	0.114
1997	1.314***	0.114
1998	1.248***	0.112
1999	1.455***	0.086
2000	1.552***	0.085
2001	1.595***	0.083
2002	1.748***	0.081
2003	1.746***	0.066
2004	1.570***	0.065
2005	2.071***	0.064
2006	1.895***	0.062
2007	2.108***	0.055
2008	2.396***	0.055
2009	2.706***	0.056
2010	2.467***	0.052
Parameters		
d_0	-1.532***	0.055
d_1	0.476***	0.053
d_2	0.196***	0.013
R-squared	0.9545	
S.E. of regression	0.132	

133 Observations.

Table 2.7: Ordered probit estimation of patent valuations using total predicted citations from Appendix A

	Without office actions			Without office actions			With office actions		
	Parameters	Marginal Effects Low	Marginal Effects High	Parameters	Marginal Effects Low	Marginal Effects High	Parameters	Marginal Effects Low	Marginal Effects High
Log forward citations[a]	0.216***	-0.016***	0.009***	0.133***	-0.006***	0.004**	0.133***	-0.006***	0.004**
	(0.019)	(0.002)	(0.001)	(0.031)	(0.002)	(0.001)	(0.031)	(0.002)	(0.001)
Log backward citations	0.017	-0.001	0.001	0.016	-0.001	0.000	0.015	-0.001	0.000
	(0.021)	(0.002)	(0.001)	(0.030)	(0.001)	(0.001)	(0.030)	(0.001)	(0.001)
Log number of claims	0.154***	-0.011***	0.006**	0.096	-0.004	0.003	0.092	-0.004	0.002
	(0.046)	(0.003)	(0.002)	(0.077)	(0.003)	(0.002)	(0.077)	(0.003)	(0.002)
Log family Size	-0.028	0.002	-0.001	0.004	0.000	0.000	0.004	0.000	0.000
	(0.032)	(0.002)	(0.001)	(0.049)	(0.002)	(0.001)	(0.049)	(0.002)	(0.001)
Log office actions							0.052	-0.002	0.001
							(0.047)	(0.002)	(0.001)
Observations		2930			1373			1373	
Log-likelihood		-3235			-1331			-1330	
LR χ^2 (p-value)		207.98 (0.000)			50.98 (0.000)			52.20 (0.000)	
Pseudo-R^2		0.031			0.018			0.019	

[a] Including estimated values for the un-observed values.
All regressions include yearly time dummy variable. Standard errors are in parentheses.

Chapter 3

Predicting the Value of Innovations

This chapter explores whether the quality (or value) of an innovation can be predicted to any degree early in its life cycle. I exploit the establishment of review committees to improve the prediction of the value of innovations before filing them as patents, to save high costs incurred in pursuing potentially invaluable innovations with the patent office. I find that despite a large effort expended by a group of leading subject matter experts, these review committees could not significantly improve their prediction power of the value of innovations that they later observe. This finding suggests that the value of innovations is unpredictable by nature, even to those with the best state-of-the-art knowledge in the area of innovation, and explains why we observe a highly skewed distribution of the value of patents in general.

3.1 Introduction

Patents have been granted in the United States since the 18th century, and have long been recognized in the economic literature as a rich and fruitful source for the study of innovation and technological change.

Employing patents as indicators of economic measures of interest started even before the patent data was widely available in a computerized format, an effort undertaken by the United States Patent Office in the 1980s. The first of these studies tried to explain the growth in aggregate efficiency of the U.S. economy by relating it to patent statistics (Schmookler (1952)). It was established that patent counts are an indicator of inventive activity. In order to try and understand what else patent statistics can measure, several studies followed to look for correlations between patent count and R&D expenditures, productivity growth, profitability or the stock market value of a firm (Scherer (1982), Bound *et al.* (1984), Pakes and Griliches (1984), Acs and Audretsch (1987)). Some of the main conclusions from these works are that R&D expenditures and patent counts exhibit a strong correlation at the cross-sectional level across firms, but this relationship is weaker in the within-firm time-series dimension.

Although extremely valuable, one of the major drawbacks of these early works was that they relied exclusively on patent counts. It has long been known that patents differ greatly in their inventive and economic significance. Many of them reflect minor improvements and little or no economic value, some of them prove to be valuable and even fewer prove to be extremely valuable. Moreover, the distribution of such values was shown to be extremely skewed (Schankerman and Pakes (1986)), by using the patent renewal data in some European countries where annuity costs rise during the end of a patent's lifetime. Thus, patent counts were empirically established to be seriously limited in the extent to which they can capture the underlying heterogeneity of patent values (Griliches, Hall and Pakes (1987)). In an attempt to overcome these limitations, researchers explored using other data items contained in patents themselves. Patent citations were suggested as one possibility to tackle such heterogeneity, initiated by the finding that patent citations appear to be correlated with value of patents (Trajtenberg(1990)). Other works followed to learn the exact role of patent citations among other factors in determining the patent quality, such as firm level R&D expenditures, number of claims per patent, number of countries a patent is filed in, etc. (Hall, Jaffe and Trajtenberg (2001), Lanjouw and Schankerman (2004) and Hall and Torrisi (2007)).

Why do we observe such skewness in the distribution of patent values? One reason is the cost structure of patents in most countries, including the United States. Once a patent is filed with the patent office, it takes several years and a large up-front cost to get the patent granted. After the grant, the annuity cost payments to keep the patent alive are very small in comparison. Thus, clearly once a patent is granted, there is a diminishing incentive for firms or individuals to abandon their rights and save costs in light of any uncertainty about a patent's value. The incentive for cost saving is much higher earlier in the life cycle, before the hefty filing, prosecution, and grant costs are incurred. The lifetime fee structure for a typical U.S. patent to be paid to the patent office is shown in Figure 3.1, illustrating that roughly 70% of a patent's cost is incurred by the time it is granted, i.e., approximately within the first five years of its life. The ratio of the early cost increases even further if the attorney cost for drafting prosecuting the patent applications before grant is also taken into account. In addition, if a U.S. patent is filed in other foreign countries, the filing must occur within 1-2.5 years of the U.S. filing date[1], further adding a significant cost burden early in the patent's life cycle.

This observation begs the question whether value of innovations can be predicted to any measure by the best set of experts early in the innovation life cycle? If so, then firms should employ a larger effort before filing patents with the patent offices in order to save the high cost incurred early in a patent's life cycle.

I study a sample data set from an organization that indeed employed a policy intervention to try and predict the value of innovations generated by its

[1]Under the Patent Cooperation Treaty (PCT), an applicant may file for a patent application in the PCT office within 1 year of the U.S. filing date. The PCT application can then be converted into patent applications for individual countries that have signed onto the PCT treaty, within 2.5 years of the U.S. filing date. Otherwise, an applicant may wish to skip the PCT application and file a patent application directly in the offices of individual countries within 1 year of the U.S. filing date.

inventors, before filing them. Review Committees (RCs) were established in different groups of the organization at different points in time. We are able to observe the decisions that were taken by the RC. In addition, the value of patents is later revealed in their life cycle based on received citations, and based on evaluation of subject matter experts. Thus, in light of the potential value of the patents related to the early innovations being known at a later time, we try to estimate how successful the RCs were in 'predicting' this value.

The RCs were set up for reasons unrelated to inventive outcomes, but rather as a potentially cost effective measure to mitigate the rising cost of filing and maintaining patents due to an exponentially rising number of generated innovations, a trend faced by several firms today. Furthermore, they were unannounced to the inventors and were set up at different times across two different groups due to logistical reasons. Thus the implementation of this policy intervention resembles a natural experiment and we employ a difference-in-differences strategy to compare the group that was treated with the policy with that which was not, in our outcome variable of interest which is the change in the ratio of valuable innovations filed. We find that the RCs did not have a significant impact on predicting the value of innovations, in spite of the large amount of effort expended by them. We further explore the possible reasons for this finding by understanding the change in other outcomes that could be related to value of innovations, such as the rate of innovations submitted by the inventors and the rate of innovations that were filed as patents from among those submitted.

The findings of this study are relevant to organizations tackling the problem of managing rapidly rising patents and patent costs, and the patent literature as a whole, as they hint towards whether we can predict the value of innovations. The answer to this adds to a greater understanding about the innovation life cycle. The findings are also helpful towards understanding the optimal patent fee structure that should be implemented by patent offices around the world, i.e., whether the patent cost should be more front-loaded or end-loaded through a patent's life cycle.

The chapter is organized as follows: Section 3.2 describes the background about the relevant patenting process in the United States as well as the process specific to the organization. Section 3.3 explains the policy intervention implemented to help predict the value of innovations. Section 3.4 describes the data used in this study. Section 3.5 discusses the estimation strategy and the results. Section 3.6 concludes.

3.2 Background

In this section, we first briefly describe the relevant workings of the patenting process in the United States. Second, we describe the process of reviewing and filing patents specific to the organizational structures that we are studying.

3.2.1 The U.S. Patent Process

By definition, a patent is a legal right conferred upon the creator of an invention by the government for the sole right to make, use, and sell that invention for a set period of time. In the United States, patents are issued by the Patent and Trademark Office (PTO), which is a part of the department of commerce. Each patent contains a 'specification' that describes the background and what the innovation does that has never been done before, and lists one or more 'claims' that define the legal scope of protection granted to the patent. Other countries have similar systems, although the details of how they implement the patent concept vary.

To get a U.S. patent, the inventor(s) file an application with the PTO and pay a corresponding filing fee. In order to receive a patent grant, a PTO examiner must determine that the innovation meets the standards of patentability. The examiner's job, in effect, is to compare the innovation covered by the application to what is called 'prior art', a legal phrase that covers everything known before the time of the patent application. If the examiner concludes that the claims cannot be granted, the applicant has the opportunity to redraft the claims, usually by making them more restrictive, and thereby distinguishing them from the prior art. Thus, the process of patent examination is largely one of negotiation between the examiner and the applicant. In principle, the 'granting' rate of patent applications is fairly high, but the claims that are ultimately granted at the end of this negotiation may be narrower in scope, limiting the overall value of the patent to its holder. Typically, the negotiation process, also known as 'patent prosecution phase', takes 2-5 years. During this phase, each correspondence between the applicant and the examiner is called an office action, and an office action fee needs to be paid by the applicant to the PTO. Thus, for a patent filed at any given date, the exact nature of the claims that are finally granted will be fully known only at granting, after 2-5 years of filing. When a patent is finally granted, the patent holder must pay an issuance fee to the PTO.

The date a U.S. patent is filed with the PTO is termed as the patent's 'filing date'. However, another date, termed as 'priority date', which may be the same as or earlier than the filing date, is used to establish the novelty of a particular innovation relative to the prior art. An applicant may file a 'provisional' patent application at no cost, and then file a full-length application with the PTO, *within one year*, when s/he has to pay the filing fee. In this case, the priority date is the date of the provisional application filing, and the filing date is the date of filing with the PTO. A patent expires 20 years from its filing date. During fixed periods throughout the patent's lifetime, an annuity fee needs to the paid by the patent holder to the PTO, to keep the patent alive.

3.2.2 Patent Process Specific to Innovative Organizations

Patents have become exceedingly important for innovative firms, especially since the early 1980's, as various patent and administrative reforms have led to strengthening the legal value of patents. In the U.S., a key step in the direction towards stronger IP protection was the creation of a specialized Court of Appeals of the Federal Circuit (CAFC) in 1982 (Jaffe and Lerner (2004)). Starting from the 1980's the trend of cross-licensing agreements and litigation suits amongst firms has grown exponentially.

We observe data from an organization that generates IP and engages and licensing and cross-licensing agreements much like most large organizations industry. Patents eventually expire, and any technology by nature becomes obsolete, therefore innovative organizations rely on constantly renewing their portfolios with new and valuable inventions as well as patents. In essence, innovative organizations in fast-paced technology areas place a high value on generating and maintaining valuable patents.

The process of innovation of a typical organization flows as follows:

Step 1: The inventor has an idea and submits an online form documenting the idea. A patent attorney is assigned to this idea. Under the first-to-invent system followed by the U.S. patent system at the time of writing, the date on this form is typically the first documented record of this idea, and thus serves as the priority date of the innovation.

Step 2: The job of the assigned patent attorney is now to follow-up on the idea and decide upon the merit of the innovation by interviewing the inventors and searching for prior art. If the idea is novel, the patent attorney drafts and submits a patent application to the PTO. The patent attorney also oversees the prosecution of the patent, i.e., follows through the entire process of negotiation with the examiner at the PTO.

Step 3: Once the patent is granted, or after several years from the filing date, the value of the patent is ultimately revealed. This may happen through received citations, business transactions, or evaluation by subject matter experts that may review the patent to determine its potential economic value.

We group these ratings of the patents in a scale of three: high, medium, and low. Consistent with previous findings in the literature on the overall distribution of the value of patents (Pakes and Shankerman (1984), Shankerman and Pakes (1985)), the estimated value of patents in the sample also exhibits a highly skewed pattern. Given that most of the revealed valuations in Step 3 are carried out after the patent is granted, or close to granting, the patent valuation is estimated with the certainty of claims that are ultimately granted at or towards the end of the prosecution process, as well as more knowledge about the actual technology evolution since the filing date. In essence, these ‘post’-ratings are the most reliable estimate of the economic value realized by the patents.

3.3 Policy Intervention

In this study, we try to estimate the impact of a policy intervention that was adopted to predict the value of patents, *prior* to filing them. The motivation of this intervention was to differentiate between potentially valuable and non-valuable patents prior to paying the variety of fees (namely, the filing, office action and annuity fees) and cost of human effort incurred during the lifetime of each patent. As the number of patent applications filed by firms rises rapidly, a significant amount of cost savings both in the variety of fees as well as human capital in the number of patent attorney hours can be gained by avoiding filing of non-valuable innovations. As an added benefit, the filing of potentially valuable innovations can be ensured.

Review Committees (RCs) were established in different groups at different points in time. The flow of the innovation process after this modification is depicted in Figure 3.2.

In addition to the filtering, the committees also assigned a 'pre'-rating to monitor the value of patents that it decided to file with the PTO. Innovations pre-rated high are deemed as potentially most valuable, followed by medium and finally the low value innovations. The pre-rating thus gives an early measure of the value of patents generated out of these innovations, but is not considered as a measure of the economic value of the patents, which is assumed to be revealed per the later ascribed evaluation.

The establishment of the committees was decided from a separate entity than from where technical innovations take place, and was announced to majority of the employees, in particular the inventors, only a few weeks before its initiation. Thus, for the inventors the intervention was an exogenous change, as the inventors could not have predicted the establishment of a RC and adjusted their behavior (for e.g., by changing the quality of their submissions) accordingly. Also, the reason for the establishment of committees was not driven by particular group(s) generating a higher number of non-valuable patents. It was simply motivated in response to the number of steadily increasing patent filings and thus employing more potentially cost effective measures to control the cost of filing and maintaining a patent portfolio, by weeding out non-valuable ideas in the beginning of a patent's life cycle.

The committees were a relatively large intervention in magnitude. Each committee was attended by team leads, subject matter experts, patent attorneys and paralegal support staff. Inventors would usually attend to present and defend their innovation, and a decision was made based on the merit of the innovation, based on the best possible prediction of the future technology evolution (i.e., whether the idea may be valuable in the future or not) of those present into account.

Due to logistical reasons, the RCs were established gradually across different groups, first in what we would call the 'treatment group', and then more than two years later, in what we would call the 'control group'. Together, these two groups constitute the majority of the organization's patent generation. Both groups typically work on the same technological innovation. Hence, patents from both groups are of overall comparable technological and economic value.

We are able to exploit this natural experiment in order to measure the effect of this policy intervention in predicting the value of innovations, by comparing the aggregate ratio of the valuable to total number of innovations (based on the actual estimated value of patents defined by the patent ratings), before and after the intervention. If the RCs were a successful filter in identifying the invaluable patents and avoid filing them, they would improve the ratio of valuable innovations observed later in time by patent values. Learning whether the RCs had an impact in increasing the overall value of the portfolio, and the measure of that impact, helps towards understanding how much effort to exert in predicting the quality of innovations ex-ante, early in the life-cycle of an innovation. If the RCs did not have an impact, it leads us to question why such a large intervention would fail in being effective.

3.4 Data

The data in our sample covers a representative sample of the innovations submitted and filed by the treatment and control groups. As described earlier, each inventor submits an idea describing the innovation, based on which a provisional application is filed. If the idea passes the RC filter successfully, an application with the USPTO is filed within one year. In reality, each innovation can spawn more than one application, and each application in addition can spawn more than one patent. In the terminology of patents, continuations or divisionals corresponding to the same application can result in multiple patents. However, the RC determines whether to file or not for each individual *innovation* (not application or patent). Thus, our data-set lists all the *innovations* ever submitted by the inventors in the sample.

For each innovation, a status field informs us whether the innovation was filed, not filed, or converted into a trade secret[2].

The date of submission, or the priority date for each innovation, as well as the date of filing with the PTO is also known. The number of patents corresponding to each innovation helps us determine the total number of patents.

For each innovation, the pre-rating assigned to the innovation by the RC, as well as the post-rating assigned to the patents spawning out of the innovation is known. The post-rating is assigned per patent, and may occasionally differ across the patents spawned by the same innovation. In such cases, we use the highest post-rating across the patents corresponding to the same innovation. This is because even if an innovation generates one patent with a high enough value, the innovation should be considered worth filing by the RC. The pre-rating assignments are used for other decisions, since they are the best measure of an innovation's and its corresponding patent's quality during the filing decision in the absence of a later ascribed value. During the later post-valuation, sometimes the pre-rating of a patent may be revised. It is thus imperative that we use the pre-rating that were assigned by the RCs before they were revised. We do this by pulling the original

[2]Trade Secrets are an alternative tool for firms and entities to protect their innovations. We do not report trade secrets for our sample.

pre-rating for each innovation, within a year of its submission date.

Determining the group of origin per innovation required certain assumptions. Every innovation can have one or more inventors, the latter being more common. While typically all the inventors belong to the same group within the organization, there are cases where they may belong to different ones. We determine the group of an innovation's origin based on the identity of the primary inventor. A unique identifier that is assigned to each inventor helps us track the primary inventor's current group. It is assumed that the inventor's current group was the one at the time of innovation's submission and filing.

Finally, as patents take a few years to be granted by the USPTO, we clip the data at the date of January 2006, for including only the innovations whose corresponding patents have likely been granted or are close to being granted, and thus the patent values have been assigned in the period of high certainty about the claims.

3.4.1 Summary Statistics

Table 3.1 reports the summary statistics for the sample dataset, and for the two groups - treatment and control. Column 1 reports the total values for the entire sample, and Columns 2 and 3 report the values for the treatment group and the control group respectively.

In Panel A, the first row reports the percentage of innovations that were filed. Among the total submitted innovations, the decision on roughly 52% is to file as patents and the rest are either rejected (the innovations are not pursued any further) or are protected as trade secrets. The acceptance rate (i.e., the ratio of innovations chosen to file as patents) across the two groups does vary, with the control group filing 59% of its received submissions, roughly 9% more than the treatment group. Panel A also reports the distribution of pre-rating assignments for the innovations in the overall sample, and for each of the two groups, as assigned by the RC. The pre-rating roughly represents the predicted value of the innovation early in its life cycle. The average pre-rating is also higher for the control group as compared to treatment, while the variance is also higher for the control group, producing a higher percentage of high value innovations as well as a higher percentage of low value innovations.

All the innovations that were filed do not have an observable post-rating. Panel B reports the subset of innovations that have been reviewed by the subject matter experts and been ascribed a valuation. This is the data set that we use for estimating the impact of RCs, as for only these innovations we observe their 'true' value, which we can compare to the value predicted by RCs in making its decision on whether to file innovations or not. The post-rating distribution also shows the same trend as the pre-ratings, with the control group having a higher mean as well as a higher variance, although to a far lesser degree. The pre-rating distribution for the reviewed innovations is quite comparable across the two groups (also represented in Figure 3.3). This is useful to demonstrate that there was no significant bias in selection of the rated patents, as chosen from one division versus from another. For example, the possibility that a much higher percentage of high value innovations from one division or a much higher percentage of low value innovations from the other may represented by the subset of post-rated patents, is ruled out.

In summary, several conclusions are apparent from Table 3.1. The number of innovations submitted and filed are very similar across the two groups we wish to compare. The acceptance rate of roughly 50% in the treatment group, and of 59% in the control group is comparable. We can generalize that the innovations that were not filed were actually rejected - either by the individual patent attorney or the RCs - as deemed unworthy of pursuing further. Only a subset of the total innovations have been reviewed and ascribed a post-rating, and the number of reviews in the sample-set are distributed evenly across the two groups. The control group produces both relatively higher high rated and relatively higher low rated innovations than the treatment group, while the average rating is the same across the two. Finally, the pre-rating distribution among the reviewed cases shows that a very similar percentage of pre-rating mix has been reviewed from both the groups, and thus the subset of data that we are using is a good representative of the two groups.

3.5 Specification and Estimation Results

3.5.1 Empirical Strategy

The RC was first established in the treatment group, and was established more than two years later in the control group. The period of time during which neither group had a RC is referred to as the pre-treatment period, the period when the treatment group had a RC and the control group did not is referred to as the comparison period, and finally the period when both groups had a RC is referred to as the post-treatment period.

The main challenge we face is isolating the impact of RCs on our outcome variable of interest, the ratio of 'good' innovations, namely the number of innovations with post-rating $\geq$ medium over total number of innovations, as observed well after the RCs decision. It is likely that the change in this outcome may be driven by several factors unrelated to the establishment of RCs. In particular, the two groups may differ in the inherent incentives and opportunities faced by the inventors. For example, it is possible that the control group employees may face higher incentives as well as opportunities to produce more and higher quality patents. These group specific effects are unlikely to change quickly with time for large organizations. Similarly, there may be time trends, both organization and technology specific, that may drive the ratio of 'good' innovations. Studies have shown that during the beginning of any technology several key ideas are generated, and as the technology grows the improvements become incremental (revolution versus evolution). Thus, a technology maturity trend may be at work to drive down the ratio of 'good' innovations regardless of the RCs' efforts. Other trends, such as the change in company atmosphere may have an impact. As the size of an organization grows, the investment in innovation activity is likely to grow. Indeed as an organization grows in reputation and is able to attract higher quality of employees in its technology area, innovations may improve in their quality. All of these trends are likely to impact the two large and important groups of the same organization, working on the same technological innovation, more-or-less equally.

In order to isolate the impact of RCs on the ratio of 'good' innovations, we can employ the difference in differences (DD) strategy between the two groups for the comparison versus the pre-treatment period. The first difference eliminates the group specific effects, and the second difference eliminates the common time trends. The usual underlying assumption for DD strategy is that the treatment and control groups would have exhibited similar changes in the ratio of 'good' innovations with time, if not for the establishment of the RCs. Therefore, we further control for the possibility of treatment and control group specific factors by exploring various factors that could differentially impact the outcome variable for the two groups (for example, the growth in revenue generated as well as the growth in number of employees per division would have an impact on innovation specific spending and innovative activity).

3.5.2 Treatment and Control Group Comparison

Before we can employ our estimation strategy, we must compare the treatment and control groups prior to establishment of RCs, for the characteristics of interest. Table 3.1 reports the baseline statistics related to innovations for both treatment and comparison groups, i.e., for both divisions prior to the establishment of RCs. We see that the null of equality across the two groups cannot be rejected for average post-rating or the average pre-rating.

We further perform a chi-square test to check the distribution of the post-rating rating and pre-rating for the reviewed inventions (with an assigned post-rating). Although the control group demonstrates a higher percentage of very high value patents (16.41% with post-rating = high) than the treatment group (13.45% with post-rating $\leq$ high), it also demonstrates a higher percentage of low value patents (32.83% with post-rating = low) than the treatment group (29% with post-rating=low). The high p-value (0.14) of the chi-squared test suggests the support to null (equality) hypothesis of the two samples being drawn from the same distribution. The pre-rating distribution across the two groups is also comparable, with the chi-squared test yielding a high p-value (0.48) in support of the null hypothesis.

As noted in Table 3.1, not all filed innovations have been reviewed and been assigned a post-rating. If the selection of innovations reviewed was heavily biased in a certain direction, for example, if only higher quality patents had been reviewed (for example, by starting with the review of the highly rated patents) or vice versa, or if mostly control group patents had been reviewed or vice versa, or if mostly higher quality control group patents but lower quality treatment group patents had been reviewed, then the pre-and-post treatment comparison of the treatment and control groups would pose a problem. Figure 3.3 shows the distribution of pre-ratings that have been reviewed and assigned an innovation value both across the entire sample, as well as in the treatment and control group in a bar chart format, to demonstrate that there is no significant bias in any direction for the patents being chosen for review.

Thus, we can proceed for the estimating the impact of RCs on the ratio of 'good' innovations by comparing the two groups pre-and-post treatment using the DD strategy.

3.5.3 Difference-in-Differences

To measure the impact of RCs on the ratio of 'good' innovations, we begin with the following equation:

$$Y_{it} = \beta_0 + \beta_1 \text{Treat}_{it} + \beta_2 \alpha_i + \beta_3 \delta_t + \epsilon_{it} \tag{3.1}$$

Where, Y_{it} is the ratio of 'good' innovations in group i=(Treatment, Control) at time t (prior to and after June 2000). On the right hand side, Treat_{it} is a dummy representing the treatment, i.e., the establishment of RCs, and thus takes on the value of 0 for the pre-treatment period and 1 for the treatment group during the comparison period. α_i is a vector of all group specific effects (such as differing incentives to inventors across different divisions) and δ_t is a vector of the common time trends across the two groups (such as technology maturity, organization specific changes etc.). The level of 'treatment' is at the group level.

The first within group difference eliminates the group specific effects (α_is) and a second difference of difference across the groups eliminates the common time trends (δ_ts), leaving us with the treatment dummy alone.

$$\Delta(\bar{Y}^{\text{Treat}} - \bar{Y}^{\text{Control}}) = \beta_1 \text{Treat} + \Delta(\epsilon^{\text{Treat}} - \epsilon^{\text{Control}})) \tag{3.2}$$

Thus, β_1 measures the isolated impact of the RCs on the change in the outcome variable of interest. Alternatively, adding time and group dummies implies that the coefficient on the interaction between the time and group dummy variables identifies the treatment effect, or the impact of RCs on change in ratio of 'good' innovations.

Table 3.5 shows the estimates of equation (3.2). The outcome variable is always the ratio of 'good' patents. We vary the threshold for differentiating good from bad patents based on the post-ratings from (i) to (ii). Since the organization considers patents with post-rating $\geq$ medium as valuable, we first consider that threshold in specification (i). We also consider the alternative threshold for differentiating good patents as those with post-ratings= high in (ii). Row 1 of the table presents the time dummy variable to control for the time trends, Row 2 represents the group dummy variable to control for the conditions specific to the group, and the interaction term captures the impact of the treatment, i.e., establishment of the RC. The impact of the RC on differentiating between innovations with post-rating $\geq$medium and $<$medium (column (i), Row 3) was -3% with a standard error of 5% on the coefficient, i.e., the measure of the treatment is small, negative and statistically insignificant. The same results - small and statistically insignificant impact of the treatment effect - are observed for the ability of the RC to differentiate between innovations with post-rating $\geq$high and $<$high. In column (iii) and (iv) we control for the pre-ratings that apriori give us some information about a patent's value. The general rule is that low pre-rated patents are likely to be non-valuable, and high pre-rated are likely to be very valuable. Medium predicts a value between the two extremes of a somewhat comparable magnitude. Since patents with post-rating$\geq$medium would most likely have a pre-rating of high or medium, we set the pre-rating control variable to low for these pre-ratings in column (iii). Similarly, patents with post-rating$\geq$high would most likely have a pre-rating of high, we set the control variable for pre-rating to high for these column (iv). Even when we add controls for the pre-ratings, we see that the magnitude and the standard error of the treatment effect do not change significantly, thus eliminating the possibility of an omitted variable bias.

The results indicate that after the establishment of RCs, there is no statistically significant change in the ratio of 'good' innovations. Thus, a large resource-rich intervention convening a group of experts early in the innovation process entirely fails to improve the predictive power of the future value of innovations.

In order to further investigate other channels that may explain the impact of the RCs, we check if perhaps their establishment had an impact on the rate of submitted innovations (per quarter). Some innovators may be deterred from submitting their innovations in anticipation of having to defend their innovation in front of elite and critical members of the review committee, while others may be encouraged to submit them for gaining higher visibility with the review committee members, and also due to now gaining exposure into how their innovations are handled. We first define our outcome variables of interest - the submission and acceptance rate - as the number of submissions per quarter and the number of patents filed per quarter respectively. Column (i) of Table 3.6 shows that the impact of the RC's establishment on the submission rate, captured by the interaction term is -3.09, but with a large standard error. Thus, no statistically significant change in the rate of submissions was observed due to the RCs. In addition, column (ii) shows that even the acceptance rate of the submitted patents (i.e., the number of patents selected for filing) did not change significantly as well, with the interaction term being -5.69.

A potentially negative change in both the submission and the acceptance rate, along with no increase in the ratio of 'good' patents can be explained by the possibility that the RCs did discourage submission of those inventions that would have been rejected even by the prosecution attorneys (as was the case prior to the RC filters were established). However, among the submitted innovations they did not improve in their ability to differentiate between good and bad quality ideas.

3.5.4 Post Treatment

We further check whether any effects of the RC may show only in the long run, during later periods of time. The DD strategy can only be used when we have a control group. Since the RC was also established in the control group two years after the treatment group, the period after that date is the post-treatment period, where both the groups are treated.

Table 3.3 and Table 3.4 list the variables for the three time periods (pre-treatment, comparison and post-treatment), for both the treatment and the control groups, respectively. The first three columns represent the data for each period. The fourth column lists the difference between the pre-treatment and the comparison periods with the p-values in brackets for the hypothesis test of this difference being zero. The fifth column lists the difference between the comparison and the post-treatment periods with the p-values for null hypothesis of this difference being zero.

The treatment group data in Table 3.3 depicts that the proportion of filed innovations went up significantly from the pre-treatment to comparison period, by 8% (row 2, column 4), but went down significantly in the post-treatment period, by 18% (row 2, column 5). In order to see whether this long term decline in the filing ratio was driven by filing fewer low value patents, we focus on the difference in the pre-rating and post-rating of the evaluated patents. We find that the proportion of high patents indeed rises significantly in the post-treatment period (rows 4-5, column 5), by 3% and 8% respectively, so does the proportion of the Low patents (row 7, column 5), by 11%.

The post-treatment however, shows a different picture, with the ratio of good and bad innovations changing soon after the RC's establishment in the comparison period and the change vanishing entirely in the post-treatment period. The proportion of patents post-rated high drops by 4% (row 8, column 4) but of those post-rated medium or higher rises by 11% (row 9, column 4) in the comparison period. The proportion of patents post-rated low drops as well by 6% (row 10, column 4), thus leading to an overall increase in the value of good innovations (when the definition is post-rating $\geq$ medium).

Notably, Table 3.4 for the control group presents an almost identical picture. The proportion of innovations chosen for filing first rises in the comparison period and then drops in the post-treatment period (row 2, columns 4 and 5). A significant change in pre-rating is only observed in the post treatment period, and in the same direction as that for the treatment group (rows 4-7, column 5). The change in post-ratings is also observed only in the comparison period, with any change disappearing after the RC's establishment in this group, in the post-treatment period. The proportion of patents with a post-rating of medium go up by 12% and those with a rating of low go down by 10% (rows 9-10, column 4), leading to an overall increase in the value of good innovations.

This finding suggests that a common time trend is dictating the number of good or bad innovations being filed, and is consistent with the statistically significant time dummy observed in Table 3.5. Thus, we are able to establish that RCs did not have an impact either during the comparison or during the post-treatment period, i.e., either in the short or the long run.

Figure 3.4 further illustrates this by plotting the ratio of 'good' innovations over time for treatment and control groups. A moving averages plot is chosen for presentability. Notice that the extreme spikes during the beginning of the organization's lifetime are a result of an extremely small number of innovations in those time periods. Future periods however show no time discernible difference in the ratio of 'good' innovations between the two groups, either during the comparison or during the post-treatment period.

3.6 Conclusion

This study demonstrated that a significant amount of additional effort expended early in the innovation life cycle is unable to improve the prediction of the value of innovations. This hints to the possibility that innovations are by nature unpredictable, and policies that encourage exerting any additional effort to predict their value later in the life cycle, when some uncertainty has been resolved both regarding the technology evolution and the likely to-be-granted claims of innovations, may be more useful.

Indeed the heavily skewed nature of value of innovations revealed by earlier literature is consistent with this finding, for if firms were able to accurately predict the value of their innovations, they would not be filing invaluable innovations in the first place in order to save costs, and we would not be seeing this skewed distribution of values.

Chapter 3, in part is currently being prepared for submission for publication of the material. The dissertation author was the primary investigator and author of this material.

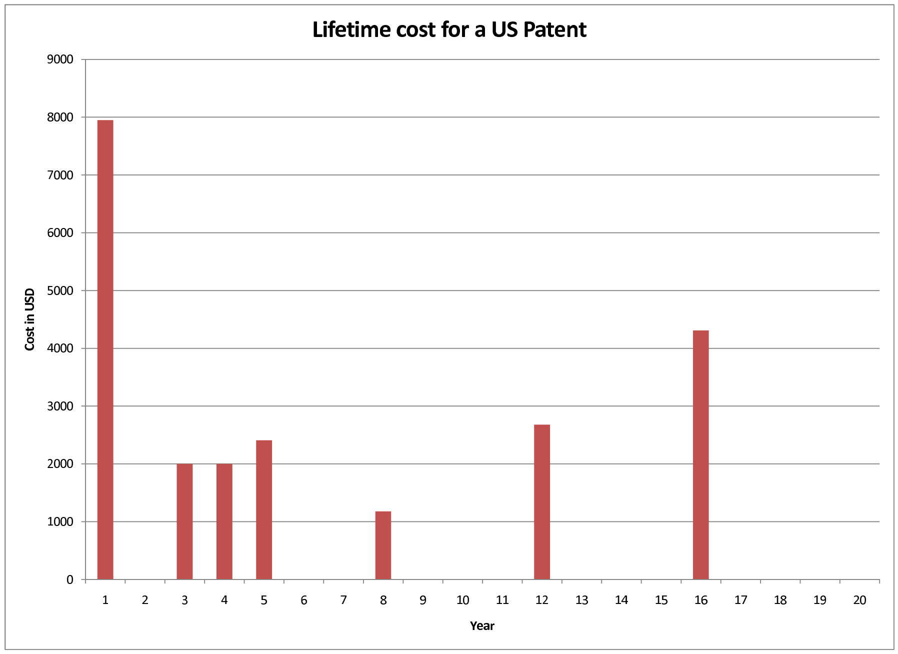

Figure 3.1: Lifetime cost for a U.S. patent

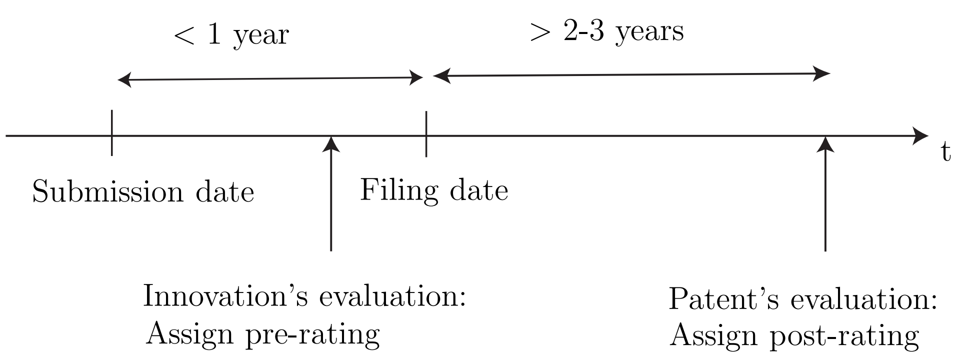

Figure 3.2: Innovation timeline

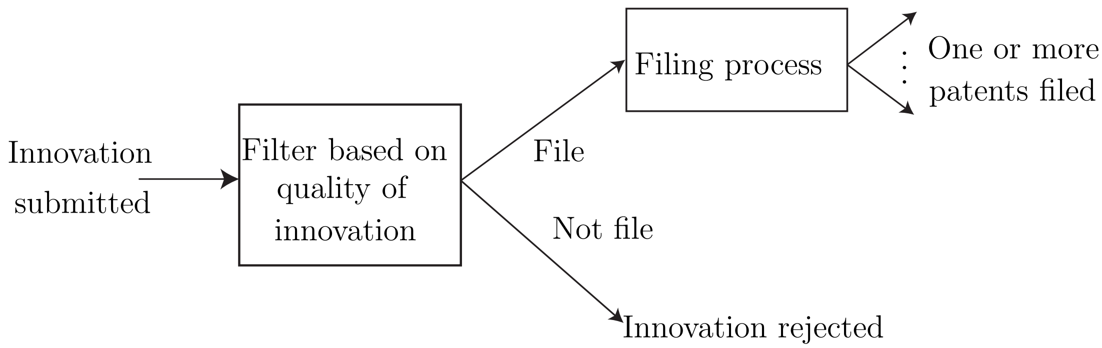

Figure 3.3: Relationship between innovations and patents

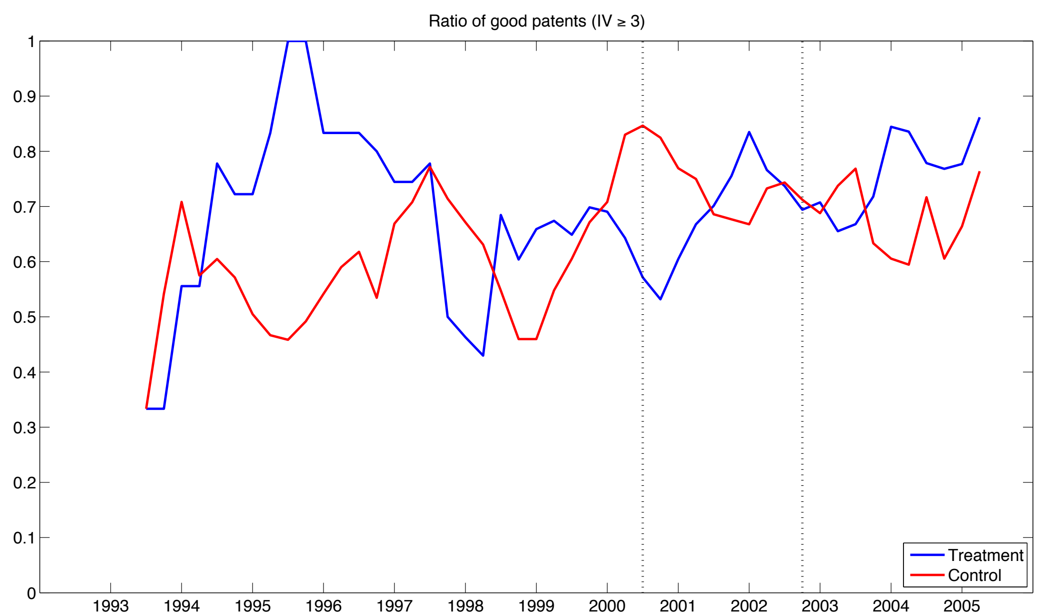

Figure 3.4: Ratio of good inventions vs time (3-point moving average)

Table 3.1: Descriptive statistics

	Treatment	Control
A. ***Total Innovations***		
Filed	50.02%	59.07%
No. of innovations pre-rated:		
High	32.88%	49.36%
Medium	50.27%	32.62%
Low	16.85%	18.12%
B. ***Reviewed Innovations***	20%	23%
Number of post-rated:		
High	9.78%	15.82%
Medium	64.48%	53.56%
Low	26.20%	30.60%
Number of pre-rated:		
High	48.00%	45.70%
Medium	20.60%	21.20%
Low	31.40%	33.50%

Table 3.2: Pre-treatment comparison

	Treatment Group	Control Group	p-value (H_0 : Diff = 0)
No. of innovations			
Filed	63.45%	63.94%	
Reviewed	57.17%	64.54%	
Post-rated			
High	13.45%	16.41%	
Medium	53.45%	46.51%	
Low	33.09%	37.05%)	$\chi^2(3) = 5.52$ p= .1376
Pre-rated			
High	23.41%	34.59%	
Medium	44.54%	27.50%	$\chi^2(3) = 4.99$ p= .48
Low	31.98%	37.88%	

Table 3.3: Pre-and-post treatment comparison

	Proportions in population (standard error)			(p-value)	
Innovations	(I) Pre	(II) Treatment	(III) Post	(II)-(I) Diff	(III)-(II) Diff
Filed	0.63 (0.02)	0.72 (0.02)	0.54 (0.02)	$+0.08^{***}$ (0.00)	-0.18^{***} (0.00)
Pre-rated	0.52 (0.02)	0.66 (0.02)	0.53 (0.02)	–	–
Post-rated	0.36 (0.02)	0.34 (0.02)	0.20 (0.01)	–	–
No. Pre-rated					
High	0.15 (0.02)	0.14 (0.02)	0.21 (0.02)	-0.01 (0.29)	$+0.08^{***}$ (0.00)
Medium	0.44 (0.02)	0.47 (0.03)	0.48 (0.02)	+0.03 (0.13)	+0.01 (0.35)
Low	0.32 (0.02)	0.30 (0.02)	0.18 (0.02)	-0.02 (0.20)	-0.11^{***} (0.00)
No. Post-rated					
High	0.13 (0.02)	0.09 (0.02)	+0.08 (0.02)	-0.04^{**} (0.03)	-0.01 (0.31)
Medium	0.53 (0.02)	0.65 (0.03)	0.70 (0.03)	$+0.11^{***}$ (0.00)	+0.05 (0.06)
Low	0.29 (0.03)	0.23 (0.03)	0.19 (0.03)	-0.06^{**} (0.04)	-0.04 (0.07)

Table 3.4: Pre-and-post comparison for the control group

	Proportions in population (standard error)			(p-value)	
Innovations	(I) Pre	(II) Treatment	(III) Post	(II)-(I) Diff	(III)-(II) Diff
Filed	0.64 (0.02)	0.77 (0.02)	0.61 (0.02)	$+0.13^{***}$ (0.00)	-0.15^{***} (0.00)
Pre-rated	0.56 (0.02)	0.66 (0.02)	0.60 (0.01)	–	–
Post-rated	0.41 (0.02)	0.33 (0.02)	0.17 (0.01)	–	–
No. Pre-rated					
High	0.34 (0.02)	0.33 (0.02)	0.45 (0.02)	-0.01 (0.27)	0.08^{***} (0.00)
Medium	0.27 (0.02)	0.28 (0.02)	0.28 (0.02)	+0.01 (0.29)	0.00 (0.48)
Low	0.37 (0.02)	0.36 (0.02)	0.26 (0.02)	-0.01 (0.26)	-0.10^{***} (0.00)
No. Post-rated					
High	0.62 (0.02)	0.72 (0.03)	0.70 (0.04)	$+0.10^{***}$ (0.00)	-0.02 (0.45)
Medium	0.32 (0.02)	0.23 (0.03)	0.27 (0.03)	-0.98^{***} (0.00)	+0.47 (0.07)
Low	0.04 (0.01)	0.04 (0.01)	0.02 (0.02)	-0.00 (0.38)	-0.02 (0.07)

Table 3.5: Estimating the impact of RCs on ratio of 'good' inventions

	Ratio of "good" inventions			
Independent variable	(i) $\geq$ Medium	(ii) High	(iii) $\geq$ Medium	(iv) High
Time dummy	0.10^{*}	-0.02	0.10^{*}	-0.3
	(0.03)	(0.03)	(0.04)	(0.03)
Group dummy	0.04	-0.03	0.04	0.00
	(0.03)	(0.02)	(0.03)	(0.03)
Interaction	-0.03	-0.02	-0.04	0.00
	(0.05)	(0.04)	(0.06)	(0.04)
Constant	0.63^{***}	0.17^{***}	0.47^{***}	0.08^{***}
	(0.02)	(0.02)	(0.03)	(0.02)
Controls for Pre-Ratings	no	no	yes	yes

Note: Standard errors are given in parentheses. The sample consists of 1074 observations with inventions that have both a pre-rating and post-rating associated with them, before and after the treatment. The dependent variable in all columns is change in ratio of good inventions. The mean and standard deviation of the dependent variable are 0.68 and 0.01 respectively (for (i) and (iii)), 0.14 and 0.01 respectively (for (ii) and (iv)).

Table 3.6: Impact of RCs on submission and acceptance rates

	Number of innovations	
Independent variable	(i) Submitted	(ii) Accepted
Time dummy	42.71^{***}	34.96^{***}
	(6.98)	(4.57)
Group dummy	-5.12	-3.34
	(4.54)	(2.97)
Interaction	-3.09	-5.69
	(9.71)	(6.36)
Constant	22.82^{***}	2.10^{***}
	(3.21)	(2.10)

Note: Standard errors are given in parentheses. The sample consists of submission and acceptance rates calculated over $N = 105$ quarters, with inventions that have both a pre-rating and post-rating associated with them, before and after the treatment. The dependent variable in column (i) is the submission rate and in column (ii) is the acceptance rate. The mean and standard deviation of the dependent variable are 29.3 and 2.6 respectively (for (i)) and 19.8 and 1.8 respectively (for (ii)).

Chapter 4

Patent Thickets and Patenting Activity of Startup Firms

It has been argued that "patent thickets" - an overlapping set of existing intellectual property rights (IPR) - impede innovative activity by constraining firms to operate without extensive licensing of complementary technologies. However, there is little empirical evidence of hold up caused by patent thickets on innovative activity in general and start-up firms in particular. In this paper, I first examine different indexes to measure the evidence of patent thickets and point out a potential bias in the citation based index for measuring fragmentation of IPR used in the previous literature. Then, I examine whether there is a patent hold up problem by investigating the patenting behavior of start-up firms in rapidly evolving industries displaying highly cumulative innovation. I find that if start-ups enter a technology market and choose to patent, then they acquire a higher *quantity* and a higher *quality* of patents in areas with a larger number of existing patent holders and a higher dispersion of patent rights among the patent holders.

4.1 Introduction

The important role of Intellectual Property (IP) in today's knowledge economy has been acknowledged by an extensive theoretical and empirical literature. In essence, the idea behind intellectual property rights (IPR) laws is to provide incentives for creativity and innovation, which fuel the progress of humankind. This is achieved by granting protection to inventors in the form of exclusive rights to use their innovation for a limited period of time. Patents are the most common form of IP[1] utilized by inventors for protecting their innovation.

However, there is a growing concern in the recent years that patents themselves may be becoming harmful for the innovative process. In particular, in complex technologies such as those in the high tech industry where one product is covered by hundreds of patents[2], the argument is that strategic patenting activity creates a 'thicket' of fragmented property rights that impedes R&D activity by constraining firms to operate without extensive licensing of complementary technologies[3]. Two conditions must then be fulfilled for a thicket to arise. Firstly, the production and sale of a given product involves the use of a large number of patent rights. Secondly, the ownership of those rights is dispersed. Heller and Eisenberg (1998) termed this as 'the tragedy of the anticommons', as existence of numerous rights holders leads to a socially sub-optimal outcome.

An unprecedented rise in the number of patents applied for and granted by the U.S. Patent and Trademark Office (USPTO) has provided much fuel to this debate. During the 1995-2008 period, the total number of patent applications grew at an average rate of 6.8%. This surge in patenting activity has coincided with what have been called pro-patent shifts in policy, e.g. the establishment of Court of Appeals for the Federal Circuit (CAFC) in 1982 that strengthened patent

[1]Other forms of IP protection include copyrights, trademarks, trade secrets, and industrial design rights.

[2]In the more traditional pharmaceutical industry, one patent typically covers the entire product in the form of a formula for a molecule in a new pill or drug. In contrast, even one semiconductor chip in a smart phone is covered by multiple patents, and the smart phone itself - including software, display, user interface etc. - is covered by a even higher multiplicity of patents.

[3]In this article, the term 'patent thicket' is used following Shapiro's definition: patent thickets are "an overlapping set of patent rights requiring that those seeking to commercialize new technology obtain licenses from multiple partners" (Shapiro (2001)).

rights (Gallini (2002)), and the new responsibility of USPTO for generating its own funds via the fee it collects, rather than operating as a federally funded agency (Jaffe and Lerner (2004)). Another reason for this surge is patenting activity is of course the increasing role of ideas, know-how, and innovation (in other words intangible assets) in today's knowledge economy in general, and an increase in innovative activity in specific high tech areas in particular. Regardless, frequent public debates and reports (e.g., National Research Council (2004), Federal Trade Commission (2011) and European Commission (2012)) have raised concerns over the dangers of patent thickets and called for patent reform.

This study examines whether there is a patent hold up problem by investigating the patenting behavior of start-up firms in rapidly evolving industries, namely, semiconductors, digital communications, and telecommunications. In doing so, it addresses the lack of much empirical evidence in this area by examining how the patenting behavior of firms is impacted by (i) number of existing IPR holders (or potential licensors) and (ii) the amount of dispersion of the existing IPR.

In the high tech industry, there is some evidence that firms find a way to contract around patent thickets via cross-licensing, patent pools, and other collective rights mechanisms (Merges (1996), Merges (1999), Lanjouw and Schankerman (2004)). However, these mechanisms are costly, in particular for start-up firms, that are heralded as the key drivers of innovation and economic growth. A start-up firm entering a technology area may have no patents to cross-license, and may find itself in a position to have to license complimentary technologies from multiple patent holders before beginning to build a product. To make matters worse, in the light of large patent counts, even a start-up with the best intentions, having drawn expensive multiple licenses, cannot be sure whether it may yet be infringing on an unknown patent and risk potential litigation at any point in time. This causes a serious hold up problem for start-up firms to enter a technology area fraught with patent thickets, and start innovating.

Despite the lively policy debate over the impact of patent thickets, and the call for patent reform in light of potentially over-strengthened patent rights[4], there is little empirical evidence on the impact of patent thickets on innovative activity, and more limited still on the impact of patent thickets on start-up firms. Ziedonis (2004) examines the relationship between firm-level patenting and a measure of the fragmentation of patent rights, by focusing on publicly traded firms in the semiconductor industry. She finds that firms acquire more patents when faced with greater fragmentation of existing patent rights among rival firms, potentially to improve their bargaining power in light of high transaction costs of obtaining licenses from multiple parties. Her results also suggest that the incentives to patent in fragmented IP markets may be more pronounced for capital intensive firms. The impact of patent thickets on R&D spending has been explored by Bessen and Maskin (2002), Bessen and Hunt (2003), to find that stronger patent rights have induced a decline in R&D spending in software. Noel and Schankerman (2006) find that higher fragmentation of patent rights in a technology area is associated with lower market value of firms in that area. Thus, all in all, there is some evidence for an arms-race to patents for their strategic use in highly fragmented IP markets, with a negative impact on innovative activity.

These studies, however, do not focus on the impact of patent thickets on the activities of start-up firms. It has been shown that patents can serve as a signaling mechanism for access to venture capital (Mann and Sager (2007), Hsu and Ziedonis (2007)) as well as help start-up firms experience higher growth (Helmers and Rogers (2011)). Yet, the impact of patent thickets on the activity of start-up firms is ambiguous. While the existence of a high number of patents in a given technology area may deter start-up firms from entering, such a measure may also signify an active area of opportunity and growth for innovation by new entrants. By the same token, while the existence of fragmented IP rights in a technology area may provide incentives to large (and capital intensive) firms for strategically increasing their patenting (to reduce transaction costs of licensing from multiple

[4]Whether the patent rights are too strong or too weak is not a new debate. Throughout the history of the patent systems across the world, there have been periodic debates and changes making the protection of patent rights stronger or weaker, depending on the call of the day (see Machlup and Penrose (1950)).

parties), the same may imply lower patenting activity by start-up firms (by being driven out of the market due the high transaction costs from multiple parties). On the other hand, fragmented IP rights may also imply a potential window of opportunity (or gap in the technological know how), which a start-up firm can step in to create its niche[5], thereby increasing the incentives for patenting by start-up firms.

One way to study the impact of patent thickets on start-up firms is to observe the entry and exit of firms in different technology areas with different measures of existing IP rights. A study by Cockburn and MacGarvie (2007), focusing on software start-up firms shows that firms are less likely to enter product classes with a higher number of existing patents, however, the firms that do hold patents are more likely to enter these product classes (controlling for firm and market characteristics.). Also, start-up software firms operating in markets characterized by denser patent thickets may see their initial VC funding delayed relative to firms in markets less affected by patents (Cockburn and MacGarvie (2009)).

In this study, I investigate the impact of patent thickets on start-up firms by observing their patenting activity in different technology areas. I focus on 381 start-up firms founded between 2001–05 in rapidly evolving industries, namely, semiconductors, digital communications, and telecommunications. I generate citation weighted indexes for (i) number of existing IPR holders (or potential licensors) and (ii) the amount of dispersion of the existing IPR. I first examine the commonly used Herfindahl-Hirschman Index (HHI) based measure of fragmentation of patent rights, and find that it contains a downward bias for firms with a small number of patents. This study proposes two alternative indexes to fix this issue, one counting the average number of unique assignees cited by a firm's patents, and the other counting the share of citations made to the top 4 most cited assignees. Second, I study the impact of patent thickets on both the quantity and quality of patents produced by start-up firms. A citation weighted index for the quality measurement is used.

[5]Highly concentrated IP rights in a technology area imply the existence of few strong players with a strong specialization, therefore not offering fertile grounds for innovation by new and small entrants.

I find that a higher number of and dispersion of IPR is associated with higher patenting activity by start-up firms. This is contrary to the potential effect of high transactions costs due to patent thickets holding up start-up firms from entering the market and innovating in the first place.

The rest of this chapter is organized as follows: In Section 4.2, I describe the hold up problems in technology markets due to patents in detail, and how they may apply to start-up firms. The construction of citation based measures for patent thickets is also discussed in detail. Section 4.3 includes the description of the data set used in this study. In Section 4.4, I describe the estimation method, key variables, and the result. Section 4.5 concludes.

4.2 Patent Thickets and Constructing Citations-Based Measures

It has been argued in the recent literature and policy debates that patent "thickets" in a technology area can deter innovation. According to Shapiro (2001), "a patent thicket is a dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology. With cumulative innovation and multiple blocking patents, stronger patent rights can thus have the perverse effect of stifling, not encouraging, innovation."

We experiment with two alternative measures of patent thickets to estimate their impact on both quantity and quality of patents produced by start-up firms. The first measure seeks to capture the number of holders of potentially blocking patents, or the number of potential licensors with which a firm would have to negotiate. The other measure is intended to capture the fragmentation of patent rights in the field. Both measures are computed using patent citations.

Patent citations are references to "prior art" (a legal phrase that covers everything known before the time of the patent application) and play a crucial role in the process of negotiation between the patent applicant and the examiner responsible for granting the patent. In the US, patent applicants have a "duty of candor" by law, to disclose any prior art citations to the patentability of an invention. Therefore, patent citations are very different from bibliographic citations, as they carry a strong legal significance in delimiting the property rights represented by a patent. Patent citations made by a patent give an indication of the extent to which a technological area is already covered by existing intellectual property rights, and thus potentially stifling to innovators or start-up firms who need to obtain a license to existing rights. Therefore, patent citations are helpful in determining potential licensors whose technology the patentee is building upon.

The factors determining licensing costs with potential licensors are complex. Yet, it has been argued by several scholars and policy makers (see FTC report (2011) for a summary of these arguments) that that all else equal, higher the number of licensors that a firm must negotiate licensing terms with, higher the associated cost of licensing and therefore entry and further innovation. These arguments are based on the following observations: first, higher number of licensors to negotiate with entails higher transaction costs; second, when a complex bargaining process is conducted with many licensors - each of whom have some hold up power due to ownership of blocking patent(s) - the result may be a much higher total cost due to "royalty stacking", i.e., adding the royalty of each of the essential patents (Lemley and Shapiro (2006)). However, a body of empirical work has argued that there is no evidence of royalty stacking in practice (Geradin, Layne-Farrar and Padilla (2007), Geradin and Rato (2006)).

In the context of start-up firms, an ideal empirical question would be to measure the extent to which a would-be entrant is blocked due to a significant barrier to entry posed by holders of existing patent rights. However, we are only able to observe the universe of start-up firms that did enter the market. In addition, very few firms explicitly exit the market. Therefore, I focus on observing the relationship between the patenting behavior of start-up firms and different measures of patent thickets.

4.2.1 Defining Citations-Based Indices

An ideal measure of IP rights causing a potential hold up problem would be to identify the potential patent holders positioned to exclude a firm from the use of a particular technology. As described earlier, cited patents indicate the prior-art a firm's patents are building upon, and offer a sensible proxy for identifying the set of potential licensors for the firm's invention.

We start by exploring the earliest of such measures, a citations based fragmentation index introduced by Ziedonis (2004), using backward citations to estimate whether ownership rights to a firm's complementary patents (i.e., the patents that the firm's technology is building upon) are widely distributed. Ziedonis bases this definition on the famous Herfindahl-Hirschman Index (HHI) to measure market concentration based on market shares, as follows:

$$\text{Fragmentation Index}_i = 1 - \sum_{j \in J} s_{i,j}^2,$$

where $s_{i,j}$ denotes the share of backward citations received by firms j out of the total backward citations made by firm i, i.e.,

$$s_{i,j} = \frac{\text{Number of Backward Cites}_{i,j}}{\sum_j \text{Number of Backward Cites}_{i,j}},$$

and J is the index set of the top four most cited firms. I also experiment with the top eight most cited firms for all the results reported and discussed in this study.

Notice that the measure above tries to take the fragmentation of ownership of IP in a given technology area into account. Assuming that the share of citations received by an assignee is a proxy for the importance of negotiating with that assignee, a market in which a large proportion of the citations go to a small number of firms may reduce the number of potentially important licensors. Since the index tries to capture the difficulty in reaching agreements with multiple potential licensors, the citations do not include self citations. By construction the fragmentation index is a value between 0 and 1, such that a large value of the index indicates that the ownership of the patents to which i's patents refer is highly fragmented, suggesting that thicket issues might be difficult to resolve.

The definition of this measure has been a useful step towards initiating an empirical scrutiny of the IP related hold up issues discussed in the theoretical literature. However, we find two main limitations with this measure, the second of which renders this less than useful for our study, and likely any study focusing on start-up firms. First, this index measures the same amount of dispersion for highly varying situations (see European Competition Commission Report (2011), p33). Second, I find that this index systematically realizes low values only for firms with a small number of patents. Specifically, this index typically concentrated around very high values[6] unless the firm holds a very small number of patents. A plot of the fragmentation index against the log of the total number of patents held by the start-up firms in our sample data is shown in Figure 4.1. The plot clearly depicts this bias and explains why using this index as a regressor for the number of patents would lead to a spurious positive.

The reason for the fragmentation index being clustered towards very high values is explained by the high non-linearity of the squared function, which attenuates very small values of $s_{i,j}$. In other words, when the share of backward citations received by the top four firms is small, $s_{i,j}$ shrinks, leading to very large values of the fragmentation index. This happens necessarily as the total number of backward citations increases (i.e., as the number of patents increases). A simple, albeit imperfect fix to this issue is to remove the non-linearity from the above definition, leading to an alternative specification. A plot of the fragmentation index defined as $1 - \sum_{j \in J} s_{i,j}$ against the log of the total number of patents held by the start-up firms in our sample data is shown in Figure 4.2. Notice that the values of the index no longer cluster around one, however, the index still displays a (now weaker) realization of low values for firms with a small number of patents.

In light of these difficulties, I take a step back and compute a simple measure to capture the number of potential licensors for a patenting firm. It is natural to infer that a firm is operating in a relatively "crowded" technology area with a high number of potential licensors, if the firm's patents are citing prior art owned by a large number of entities[7]. In order to compute the number of potential licensors

[6]In the (Ziedonis (2004)) paper where this index is first introduced and used, the sample statistics table over 667 panel-data observations of 67 publicly traded firms indicates the mean value of this index to be 0.89 (with standard deviation of 0.11) and a median of 0.92, indicating a clustering around very high values.

[7]Consider an analogy with academic literature. If an academic paper is citing prior literature by several other authors, presumably, the paper is contributing to a research area that is academically crowded compared to a paper citing prior literature by a limited number of authors. However, this is an imperfect analogy, as unlike bibliographic citations, patent citations carry a

in a given technology area, I compute the average number of unique assignees a firm's patents have cited, as follows:

$$\text{No\_Potential\_Licensors}_i = \frac{1}{\text{No\_Patents}_i} \sum_n \text{No\_Unique\_Assignees\_Cited}_{n,i},$$

where the summation is taken over the set of patents held by a firm i. A higher number of unique assignees suggests a higher number of potential licensors. Notice that this measure does not take the fragmentation of ownership of IP in a given technology area into account. A plot of firm-level average number of unique assignees against the log of the total number of patents for the start-up firms in our sample data is shown in Figure 4.3. Notice that the values of this index no longer cluster around one, and it displays no systematic realization of low values only for small number of patents.

4.3 Data

The ICT (Information and Communication Technology) industries - in particular semiconductors, digital communications, and telecommunications, are an important source of growth of the recent patent filings[8]. Furthermore, innovation in these industries has been touted to be highly cumulative, with new products building on a large stock of prior inventions (Shapiro (2001)), and the patent holdup problem is being discussed extensively in the context of these technologies (FTC Patent Report (2011)). Therefore, in this study, I focus on start-up firms in the industry areas of semiconductors (SIC code: 3674), digital- and telecommunications (SIC codes: 3661, 3663, 3699, 4812, and 4899)[9].

Studies on patenting activity based on the universe of COMPUSTAT firms (that are publicly traded) solely focus on the reaction of large incumbent firms to the patent landscape and policies, and can differ significantly from those of new

legal significance in delimiting the scope of a patent's rights. Therefore, prior-art cited in patents carries a clear potential economic significance.

[8] *World Intellectual Property Indicators Report 2011, WIPO Economics and Statistics Series.*

[9] The description of SIC codes can be found here: http://www.techamerica.org/sic-definition. The focus of this study is fast evolving technologies and recent technology areas, therefore only the industry areas related to **wireless** digital- and telecommunications are included, while older and more well-defined wired communications are not included.

ventures and smaller start-ups - an important source of innovation. In this study, I focus on start-up firms in the technology areas listed above. The dot-com bubble of the 1990s caused a temporary spike in the equity raised and other activities of start-up firms, that may have impacted the patenting activity. Therefore, I limit my sample to firms that were founded on or after January 1st, 2001. In addition, to allow enough time to have passed for the start-up firms to generate equity, innovate, and file for patents, I limit the observations to firms that were founded on prior to December 31st, 2005.

The start-up firm level data set in this study originates from Thomson One VentureXpert, which covers 381 start-up firms in the industry areas of semiconductors, digital communications and telecommunications, founded between 2001 and 2005. I observe the founding date of the firm, revenue, the number of founders and directors[10], the number of rounds of funding received by venture capitalists, the amount of funding received in each round, the current status (e.g.: privately held, acquired, or went public), location, and the sub-technology area characterized by 7-digit VEIC codes (Venture Economics Industry Classification), a more granular classification than 4-digit SIC codes[11].

The patenting activity for each of these startup firms is obtained via the USPTO database[12]. All the U.S. granted patents and patent applications for each firm are observed. By law, all patent applications filed at the USPTO are made available to the public 18 months after date of filing, even before a decision has been made regarding the patent's rejection or allowance towards being granted. For each patent record (granted patent or application), the application date (date the patent application's original filing at the USPTO), publication date (date of

[10]The total number of employees is not reported for over 50% of the firms in the sample. Therefore, we use the total number of founders and directors as a proxy for the size of the firm.

[11]A list of the VEIC code classifications for various industry classes and sub-classes are available at: http://www.chambersz.com/eu-network/images/stories/formi/VEICodes.pdf.

[12]A few issues had to be addressed in order to extract the patent data, that are worth discussing. First, the firm name in ventureXpert database (start-up's "registered" name) does not perfectly match the name used in the patent database (patenting entity's "assignee name"). Second, the assignee name in the patent data may be spelt in various ways (e.g., patents for "BeCeem Communications" can be listed under the assignee name "BeCeem Comm.", "BeCeem Communications Inc.", or "BeeCeem Communications"). Therefore, firm names are manually matched for merging the two data-sets, and alternative spellings and obvious misspellings of the assignee names when retrieving the patent data for each firm are accommodated.

patent application's publication), the citations *made* by the patent (backward cites), name of the assignee for each of the cited patents[13], the citations *received* by the patent (forward cites), and the publication date of the patents from which the forward citations are received, are observed.

Of the 381 firms in the sample, 205 belong to the semiconductors industry and 176 belong to digital and telecommunications, with the summary statistics of each displayed in Table 4.1 and Table 4.2 respectively. Out of the 205 semiconductor firms, 32 firms do not patent at all and out of the 176 digital and telecommunications firms, a much larger number of 85 firms do not patent at all. The 264 firms that do patent collectively received 6,117 U.S. patents and applications between 2000 and 2012, which referenced a total of 229,953 unique U.S. patents and applications.

As can be seen from Table 4.1 and Table 4.2, semiconductor firms (with a mean of 25.87 patents and applications) are more prolific patentees than digital- and telecommunications firms (with a mean of 5.07 patents and applications). A mean semiconductor firm raised an initial funding of \$6.87 million and a total equity (until 2012) of \$47.64 million over 5 rounds, while a mean digital- and telecommunications firm raised an initial funding of \$9.19 million and a comparable total equity (until 2012) of \$44.53 million over 4.11 rounds. The size (in terms of founders and board members) between the two industry areas is also comparable, with a mean of 7.6 for semiconductor firms and 6.8 for digital- and telecommunications firms. It appears that the total number of citations made by semiconductor patents, at a firm level average of 956.2, is much higher than digital- and telecommunications patents, at a firm level average of 192.78.

For the semiconductor firms, the linearized fragmentation index has a mean value of 0.62, similar to the mean computed on the sample of digital and telecommunications firms (0.54). Similarly, the average number of unique assignees cited by a firm's patents display a mean of 18.35 and 17.80 for semiconductor and digital and telecommunications firms respectively, with similar ranges and standard

[13]Since a single assignee may appear with multiple assignee names, I created a unique code for each major assignee and combined patents assigned to obvious misspellings, permutations, or abbreviations of that name to each respective code.

deviations.

4.4 Estimation Methodology and Results

In the empirical analysis that follows, my goal is to use a measure of the number of patent holders and the fragmentation of patent rights in a technology area to examine their effect on (a) the incentives to patent for start-up firms (b) the quality of patents produced by start-up firms (quality measure based on citation weighted counts).

As discussed in Section 2, an ideal empirical question would be to measure the extent to which a would-be entrant is blocked due to a significant barrier to entry posed by holders of existing patent rights. However, it is difficult (if not impossible) to find data that would allow us to observe the firms that did not enter the market. In addition, the firms that did clearly exit the market are very small (13 out of 381 filed for bankruptcy), as most continue to be active for a long time or get acquired[14]. Therefore, we are only able to observe the universe of start-up firms that did enter the market.

Among these entrants, some firms choose to patent and others do not (117 firms out of 381 do not own a single patent or application). I first try to estimate the firm level characteristics that explain which firms choose to patent. I use a simple logistic regression, where the outcome variable displays the likelihood of a firm choosing to patent (i.e., the outcome variable $Y_i = 1$ if a firm is has one or more patents, and 0 otherwise). The results in Table 4.3 reveal that the number of founders and board members, as well as the size of the initial funding, are significant in determining a firm's propensity to patent.

Next, I try to estimate the firms' propensity to patent more or less, conditional on the fact that they choose to patent (i.e., if a firm has one or more patents). Since the number of patents produced is a count variable, I use Poisson based models and estimation methods. As in Hausman et. al (1984), the expected

[14]Oftentimes, an unsuccessful start-up firm with a small number of employees gets "acquired" by a larger firm on paper, with the transaction actually implying hiring the founder(s) by the larger firm and no price paid for any other assets.

number of patents λ_i applied for by firm i is assumed to be an exponential function of firms' funding received, and other characteristics X_i, i.e.,

$$\mathbb{E}[p_i \mid X_i] = \lambda_i = \exp(X_i\beta).$$

A pure poisson model is rejected in favor of a model in which the variance is proportional to the mean due to evidence of over-dispersion (the dispersion parameter α in Table 4.4 has a consistently high and statistically significant value), and therefore I use a negative binomial distribution, a commonly used generalization of the poisson based models.

In order to control for the potential determinants of patenting across firms, I first control for well known determinants of patenting established in the prior literature, namely, firm size and R&D spending. Therefore, X_i includes key variables such as the size of the firm (i.e., the number of founders and directors) and the equity raised by the firm. Since patents hence filed by a start-up firm may effect the equity raised by the firm, I use the initial funding raised by the firm as a valid control. However, the results do not seem to change much when controlling for total equity raised instead. I also add sub-technology dummies (represented by the 7-digit VEIC code representing the industrial sector the firms are operating in) to control for potentially differing propensity to patent in different technology areas. Finally, the firms in my sample are founded in different years (2001-2005) and I need a mechanism to accommodate the fact that patent counts are made over different observation periods. Therefore, I include the log of the exposure variable - in our case the age of the firm in 2012 - in all specifications of the model, with the coefficient constrained to be one. To test the impact of the features of existing patent landscape on patenting activity, I augment the specification above with the firm specific indexes described in Section 4.2.1, for measuring the number of patent holders and for measuring the level of fragmentation of existing patent rights.

I start by using the measure introduced in this study, namely the average number of unique assignees (or potential licensors) in the backward citations of a firm's patents, as shown in Table 4.4. Columns 1 to 4 present the estimates with control variables by introducing them one by one into the specification, starting with the number of unique assignees, size, initial funding, and the sub-technology dummies. I find that patenting in a more crowded area with several owners of existing patents represents a propensity to produce a higher number of patents (column 1). Controlling for the firm's size (column 2) and initial funding (column 3) received, identifies the firm's size to be a positive predictor of patents produced by a firm. Adding the sub-technology dummies (column 4) indicates the explanatory power of the technology area the firm is operating in. The sign for the number of potential licensors is consistently positive. Focusing on column 4, the coefficient of 0.24 (with standard deviation of 0.08) indicates that if the log average number of unique assignees holding prior-art in a firm's patenting area increases by 1 unit, the difference in the log of number of patents is expected to increase by 0.24 units. Columns 5 and 6 of Table 4.4 repeat the exercise in Columns 3 and 4, by controlling for the total equity raised by a firm instead of only the initial funding received, and show an insignificant change in the results.

Table 4.5 represents the results from similar specification as described in Table 4.4, except that the fragmentation index is included as one of the controls instead of the number of potential licensors. I use the linearized fragmentation index as described in Section 4.2.1 and plotted in Figure 4.2. As described above, I introduce the control variables one by one into the specification in columns 1-4 and observe that the sign for the fragmentation index is consistently positive. Focusing on column 4, the coefficient of 2.18 (with standard deviation of 0.34) suggests that if the fragmentation index of a firm's patenting area increases by 1 unit, the difference in the log of number of patents is expected to increase by 2.18 units. Columns 5 and 6 of Table 4.5 repeat the exercise in Columns 3 and 4, by controlling for the total equity raised by a firm instead of only the initial funding received, and show an insignificant change in the results. I also use the HHI-based fragmentation index as described in Section 4.2.1, and unsurprisingly, find similar results. The sign of the fragmentation index is still positive, and the magnitude is significantly higher. The tables for these are not reported in this chapter for the sake of brevity.

In summary, the results described here suggest that start-up firms operating in technology areas with a large number of existing patentees and with a higher fragmentation of the existing patent rights, produce a higher *number* of patents. We now turn our attention to explore if the same can be said about the *quality* of the patents being produced by the start-up firms.

In order to proxy for the quality of patents, I use citation weighted patent counts as first introduced by Trajtenberg (1990) and since then used extensively in the literature (e.g. Hall, Jaffe and Trajtenberg (2001)). A simple weight of one for each forward citation received by a patent is employed.

$$\text{Weighted\_Patent\_Count}_i = \sum_{i=1}^{n} 1 + C_i,$$

Where n is the number of patents and C_i is the number of citations received by the ith patent of a firm.

I first use the observed citations as received by the patents thus far, to calculate the citation weighted count of patents acquired by a start-up firm. Table 4.6 shows that after controlling for the size of the firm (column 2), initial funding (column 3) and sub-technology dummies (column 4), the number of potential licensors enters our model with a positive sign. Thus, start-up firms are producing higher *quality* patents in a more crowded area. Controlling for total equity rather than initial funding received in columns 5 and 6 again show an insignificant change in the results.

However, I need to address the inherent truncation problem in the citation data, i.e., the fact that we observe the number of citations only until the time of observation, and therefore older patents have received more number of citations than newer patents by definition. A predictive model as described by Hall, Jaffe and Trajtenberg (2001) is employed for predicting total number of citations that would be received by a patent in its lifetime. The patent data had to be limited to patent applications published before the beginning of 2009 for at least a few years to have passed by for the patent to receive forward citations. Once the citation count is corrected, a citation weighted count using the predicted lifetime citations is computed. Table 4.7 shows similar results as Table 4.6, in that the quality of the patents produced increases with the number of potential licensors.

Similar results are displayed by controlling for the fragmentation index instead of the average number of unique assignees and are not reported in the tables for the sake of brevity.

Therefore, it appears that the start-up firms that choose to patent in crowded and more fragmented technology areas not only produce a higher *quantity* of patents, but also a higher *quality* of the patents on average.

4.5 Conclusion

In 1858 Abraham Lincoln stated that “the patent system has added the fuel of interest to the fire of genius, in the discovery and production of new and useful things”. However, lately the patent system been subject to several discussions in regulatory bodies with concerns towards the system stifling innovation, and reforms have been proposed to meet the most serious criticisms by fixing the level of patent protection.

The controversy around the patent system is not new. Most nations with a patent system enacted since the 19th century or earlier, have periodically witnessed demands for reform and even abolition of the patent system by its opponents, and calls for the need to create incentives for inventors by paying them their due reward by its proponents[15]. Today’s patent controversy places the highly innovative technology industry at the heart of the debate. With unprecedented rise in patent counts in the U.S., critics have argued that increased patent protection stifles cumulative innovation, i.e., development of technology that builds upon prior art, by swamping inventors with potential infringement lawsuits.

In this study, I analyze how the patenting behavior of start-up firms is impacted by the patent thickets, i.e., by the number of existing IP rights and by the amount of dispersion of those rights, while controlling for observable firm and market characteristics. I suggest improvements over the existing HHI-type citation based index for measuring evidence of patent thickets, that appears to be biased

[15]The U.S. itself witnessed strong skepticism towards patents during the Great Depression and World War II, while the policies enacted in 1980 and ’90s have extensively been argued as patent friendly.

by the number of patents held by a firm. I study the impact of these indexes on both the quantity and quality of patents produced by start-up firms.

The results are based on a sample of 381 start-up firms in the semiconductors, digital communications and telecommunications industries. I find that start-ups that enter a technology market and choose to patent, acquire a higher *quantity* and a higher *quality* of patents in the areas with higher number of potential licensors and a higher amount of dispersion of existing patent rights.

This result is surprising in comparison to past literature that suggests a strategic "arms race" towards acquiring patents by large firms, in areas with a higher number of existing rights holders. The idea is that if a firm needs to negotiate with a higher number of licensors in order to operate in a particular technology area, it faces higher transaction costs, and thus has an incentive to acquire more "chits to bargain with", leading to higher acquisition of its own patents. By the same token, the transaction cost may be so high for small start-up firms that they are driven out of the crowded and highly fragmented technology areas (the barrier to entry created by the high cost of licensing and potential risk of infringement is often quoted as the patent hold up problem). Instead, evidence that start-up firms acquire a more and more valuable patents in the crowded and highly fragmented technology areas, point towards the possibility that these areas imply a window of opportunity to new entrants. A gap in the technological knowhow start-up firms to create a niche, thereby increasing their patenting activity in terms of both quantity and quality.

In summary, the contributions of this study are -

- Addressing the gap in the theoretical literature by empirically investigating the potential hold up problem for start-up firms
- Proposing to measure the evidence of patent thickets using alternative indexes that address an inherent bias in the previously used HHI-based index, and
- Identifying that the patenting behavior of start-up firms suggests that patenting incentives faced by them differ significantly than for large firms. Start-

ups that do patent produce more and higher quality patents in areas more crowded and more fragmented patenting areas.

While this study contributes to the emerging literature on hold up problems in the markets for technology, it is limited in ways that can be addressed in future literature. First, the sample of firms entering a technology area represent a selection bias. Investigating the reason for why firms choose to enter a technology area would help address this selection bias. Second, any citations based index limits the sample of meaningful empirical data to firms (or firm-years in a panel data-set) with at least one patent (and therefore greater than zero backward citations), for the index to be calculated. Also, the measure of the number of potential licensors does not take into account the fragmentation of patent rights. A linear fragmentation index, counting the share of citations received by the top 4 most cited firms, is still slightly downward biased for firms with a small number of patents. There is a need of a new measure for taking into account both the number of unique cited assignees, and the ratio of citations being received by each, that is not biased by the number of patents held by a firm.

Chapter 4, in part is currently being prepared for submission for publication of the material. The dissertation author was the primary investigator and author of this material.

Table 4.1: Sample statistic at the firm level (semiconductor area)

	Mean	S.D.	Min	Max	Count
Patent Applications	25.87	50.86	0	384	
Founding Year	2002	2	2001	2005	
Total Equity Raised ($m)	47.64	84.03	9.00	996.48	
Initial Funding (received in seed round) ($m)	6.87	11.40	0.00	129.04	
Rounds of funding received	5	3	1	18	
Company Size (board members + officers)	7.60	4.21	0	21	
Total Backward Cites	956.20	3885.80	0	37075	
Current Status:					
Bankruptcy - Chapter 11/Defunct					8
In registration/Active					128
Acquisition/Pending acquisition/LBO					62
Merged/Went Public					8
Fragmentation Index (w/o squares):	0.62	0.20	0	0.89	
No. Potential Licensors:	18.35	18.67	2	111.55	

205 firms in total. 32 firms with no granted patents.

Table 4.2: Sample statistic at the firm level (digital and telecommunications area)

	Mean	S.D.	Min	Max	Count
Patent Applications	5.07	10.86	0	66	
Founding Year	2003	1.42	2001	2005	
Total Equity Raised ($m)	44.53	87.72	0.05	750	
Initial Funding (received in seed round) ($m)	9.19	24.07	0	270	
Rounds of funding received	4.11	2.78	1	14	
Company Size (board members + officers)	6.80	4.05	0	17	
Total Backward Cites	192.78	804.80	0	6990	
Current Status:					
Bankruptcy - Chapter 11/Defunct					5
In registration/Active					154
Acquisition/Pending acquisition/LBO					11
Merged/Went public					7
Fragmentation Index (w/o squares):	0.54	0.25	0	0.83	
No. Potential Licensors:	17.80	18.36	1	106.56	

176 firms in total. 85 firms with no granted patents.

Table 4.3: Logistic of determinants of patenting in start-up firms

	(I) Semiconductors	(II) Digital-Telecomm	(III) All Firms
Size	0.146***	0.125***	0.136***
	(0.050)	(0.040)	(0.041)
Initial funding	0.043**	0.037*	0.036**
	(0.024)	(0.020)	(0.023)
Log-likelihood	−83.42	−114	−220
LR χ^2 (p-value)	(0.000)	(0.000)	(0.000)
	(0.000)	(0.000)	(0.000)
Pseudo-R^2	0.078	0.060	0.067
No. observations	205	176	381

Standard errors are in parentheses.
Founding year time-dummies and VEIC sub-technology industry-dummies are included.

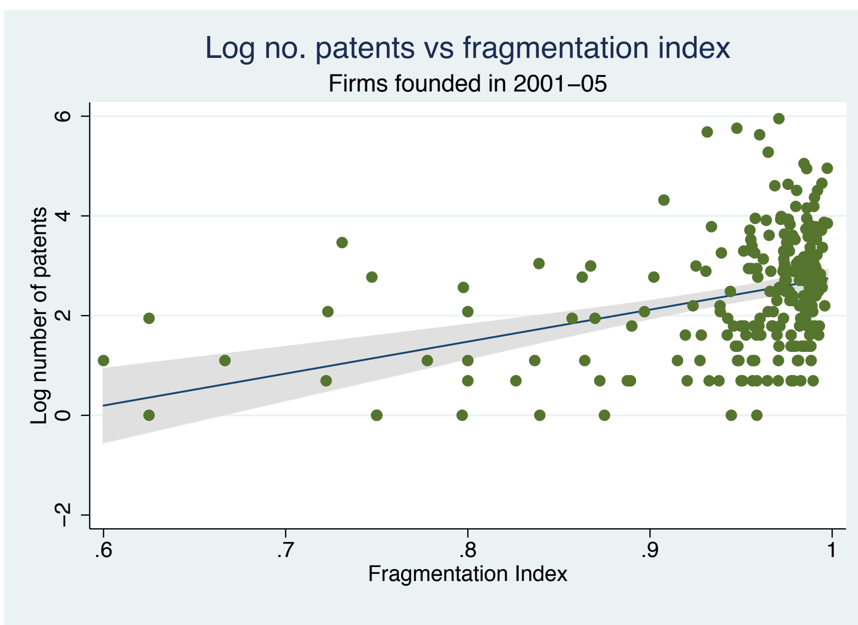

Figure 4.1: No. of patents vs fragmentation index.

Table 4.4: Negative binomial regression parameters for start-up firms

Determinants of Number of Patents and Applications						
	(1)	(2)	(3)	(4)	(5)	(6)
Log No. Potential Licensors	0.38***	0.36***	0.36***	0.24***	0.36***	0.25***
	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)
Size	–	0.05**	0.05**	0.04**	0.04**	0.03*
	–	(0.010)	(0.010)	(0.010)	(0.020)	(0.010)
Log Initial Funding	–	–	0.010	0.010	–	–
	–	–	(0.010)	(0.010)	–	–
Log Total Equity	–	–	–	–	0.04*	0.04*
	–	–	–	–	(0.010)	(0.020)
Sub-technology Dummies	No	No	No	Yes	No	Yes
Alpha	1.210	1.180	1.170	0.688	1.160	0.681
	(0.100)	(0.100)	(0.090)	(0.064)	(0.085)	(0.064)
Log-likelihood	−992.930	−989.110	−988.200	−915.250	−979.950	−907.170
Chi-square (p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R2	0.012	0.012	0.015	0.090	0.016	0.090

240 obs for semiconductor, digital- & tele-communication start-up firms founded between 2001–05.
All regressions include exposure variable accounting for different founding years.
Standard errors are in parentheses.

Table 4.5: Negative binomial regression parameters for start-up firms

Determinants of Number of Patents and Applications	(1)	(2)	(3)	(4)	(5)	(6)
Fragm. Index (w/o squares)	2.650***	2.517***	2.527***	2.182***	2.489***	2.10***
	(0.375)	(0.384)	(0.384)	(0.343)	(0.388)	(0.352)
Size	–	0.035	0.330	0.030	0.229	0.025
	–	(0.020)	(0.019)	(0.016)	(0.020)	(0.018)
Log Initial Funding	–	–	0.019	0.008	–	–
	–	–	(0.013)	(0.011)	–	–
Log Total Equity	–	–	–	–	0.034*	0.022
	–	–	–	–	(0.018)	(0.017)
Sub-technology Dummies	No	No	No	Yes	No	Yes
Alpha	1.142	1.130	1.122	0.626	1.121	0.628
	(0.096)	(0.095)	(0.952)	(0.058)	(0.095)	(0.059)
Log-likelihood	−983.03	−981.50	−980.50	−901.93	−973.09	−895.70
Chi-square (p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R2	0.012	0.012	0.022	0.100	0.022	0.100

240 obs for semiconductor, digital- & tele-communication start-up firms founded between 2001–05.
All regressions include exposure variable accounting for different founding years.
Standard errors are in parentheses.

Table 4.6: Negative binomial regression parameters for start-up firms

Determinants of citation weighted patent counts (based on observed citations)						
	(1)	(2)	(3)	(4)	(5)	(6)
Log No. Potential Licensors	0.91***	0.89***	0.88***	0.65***	0.89***	0.62***
	(0.090)	(0.090)	(0.090)	(0.100)	(0.090)	(0.100)
Size	–	0.04*	0.04*	0.020	0.020	0.010
	–	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Log Initial Funding	–	–	0.028*	0.026*	–	–
	–	–	(0.015)	(0.015)	–	–
Log Total Equity	–	–	–	–	0.045**	0.047*
	–	–	–	–	(0.020)	(0.020)
Sub-technology dummies	No	No	No	Yes	No	Yes
alpha	1.670	1.660	1.640	1.030	1.640	1.030
	(0.130)	(0.130)	(0.130)	(0.085)	(0.130)	(0.083)
Log-likelihood	−1338.63	−1336.99	−1335.43	−1261.79	−1325.86	−1252.86
Chi-square (p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R2	0.010	0.010	0.030	0.090	0.032	0.090

240 obs for semiconductor, digital- & tele-communication start-up firms founded between 2001–05.
All regressions include exposure variable accounting for different founding years.
Standard errors are in parentheses.

Table 4.7: Negative binomial regression parameters for start-up firms

Determinants of citation weighted patent counts (based on predicted lifetime citations)

	(1)	(2)	(3)	(4)	(5)	(6)
Log No. Potential Licensors	0.851***	0.838***	0.832***	0.577***	0.836***	0.557***
	(0.090)	(0.089)	(0.089)	(0.096)	(0.090)	(0.097)
Size	–	0.035	0.038	0.013	0.021	0.005
	–	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)
Log Initial Funding	–	–	0.028*	0.029	–	–
	–	–	(0.014)	(0.013)	–	–
Log Total Equity	–	–	–	–	0.047*	0.047*
	–	–	–	–	(0.020)	(0.020)
Sub-technology Dummies	No	No	No	Yes	No	Yes
Alpha	1.365	1.350	1.334	0.878	1.334	0.088
	(0.111)	(0.110)	(0.109)	(0.075)	(0.109)	(0.075)
Log-likelihood	−1340.85	−1339.31	−1337.73	−1277.30	−1331.39	−1271.70
Chi-square (p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R2	0.010	0.010	0.032	0.075	0.032	0.076

240 obs for semiconductor, digital- & tele-communication start-up firms founded between 2001–05.
All regressions include exposure variable accounting for different founding years.
Standard errors are in parentheses.

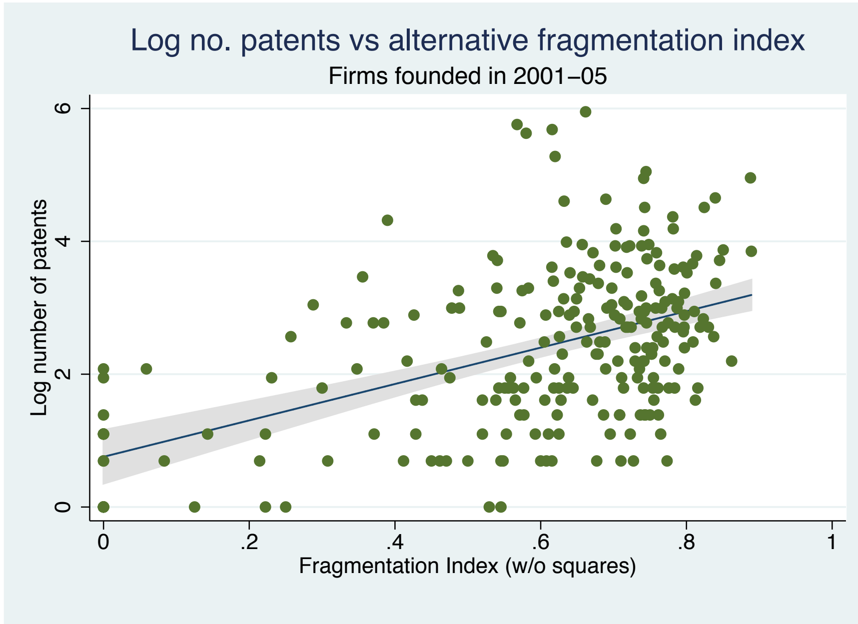

Figure 4.2: No. of patents vs alternative fragmentation index.

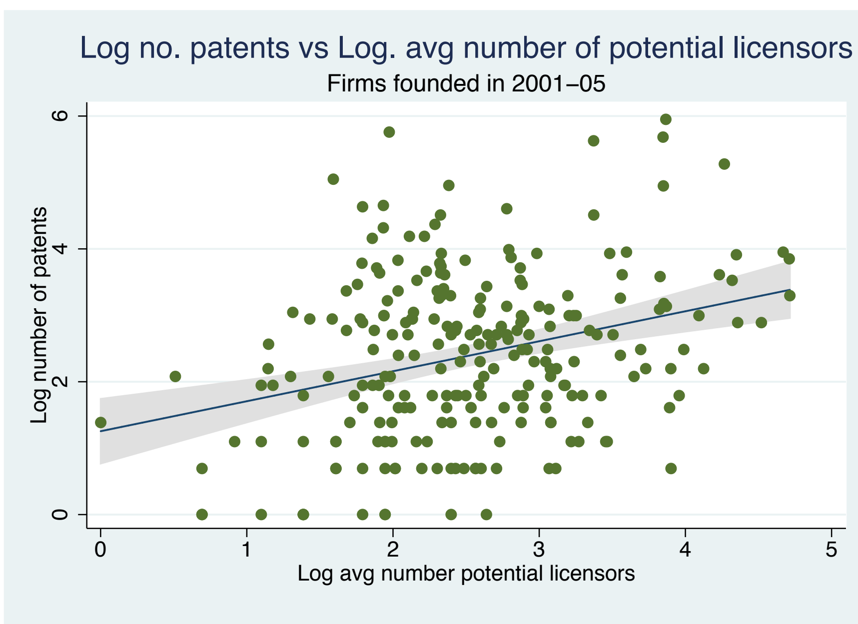

Figure 4.3: No. of patents vs average no. of potential licensors.

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